Climate Change, Cyclone Risks, and Economic Growth: A 'Business Cycles' Approach

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Abstract

Climate change is altering the global distribution of extreme weather event risks. While the direct damage costs of these changes are increasingly well-studied, their broader economic impacts remain an open question. This paper brings a "cost of business cycles" approach to estimating the welfare costs of changes in cyclone risks in general equilibrium. First, we empirically relate historical cylone strikes to (i) the distribution of idiosyncratic income shocks facing households, (ii) changes in total factor productivity, and (iii) capital losses. Our application focuses on Vietnam, utilizing the Vietnam Household Living Standards Survey (2004-2014) along with other data sources. Second, we develop a quantitative version of Krebs' (2003) stochastic endogenous growth framework based on these impact channels. The model provides a structural mapping from weather to climate impacts by accounting for households' responses to changes in the weather distribution as a function of the estimated costs of weather realizations. Third, we utilize simulations of tropical cyclones in both the current (2000) and future (2100) climate (Emanuel, 2008) to project the effects of future cyclone risks on household savings and investment behavior, growth, and welfare. The benchmark results suggest that changes in cyclone risks will depress long-run growth in Vietnam by an economically significant $0.07-0.14$ percentage points - on the same order of magnitude as recent estimates of the effect of U.S. business cycles on U.S. growth (Krebs, 2003, Barlevy, 2004). The associated welfare costs are estimated to range from $0.85-12.75\%$ of initial consumption.

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1 Introduction

Extreme weather events are a significant source of risk facing countries around the globe (World Bank, 2010). Going forward, climate change is poised to alter the distribution of these risks, with potentially large increases in tropical cyclone activity expected in some ocean basins, and decreases in others (Emanuel, 2008; IPCC, 2014). How these changes will affect economic outcomes and human welfare remains an open question.

On the one hand, a growing literature has estimated future changes in the direct damage costs of tropical cyclones events (see, e.g., review by Ranson et al., 2014). These studies typically combine sophisticated empirical estimates of the determinants of direct losses with projections of changes in the average frequency and intensity of storms due to climate change (e.g.,. Nordhaus, 2010; Mendelsohn et al., 2012; Dinan, 2017). Though essential, these studies typically do not yet address the broader economic impacts that changes in cyclone risk distributions may have.[1] In particular, a rich empirical literature has found associations between cyclones and economic growth (e.g., Hsiang and Jina, 2014; McDermott, Barry, and Tol, 2014, Cavallo and Noy, 2013, etc.), suggesting the presence of economically significant general equilibrium effects. Mapping these reduced-form output growth impact estimates into either welfare or climate change impact projections is, however, difficult. As argued by Bakkensen and Barrage (2016), different empirical estimation strategies capture different components of the overall impact of cyclones on growth. In addition, observed output growth changes need not even be of the same sign as the associated welfare effects.[2] Consequently, an alternative approach is needed to assess the welfare consequences of changes in cyclone risk distributions in general equilibrium.

This paper proposes a structural approach based on the "cost of business cycles" literature to study the costs of extreme weather event risks. The reasoning underlying this approach is as follows: (i) Natural disasters constitute a source of productivity and depreciation shocks. (ii) Climate change will alter the probability distribution of these shocks. (iii) The "cost of business cycles" literature has developed tools to quantify the welfare and growth effects of the elimination of income/productivity/consumption risks observed in modern economies (e.g., Lucas, 1987; Storesletten, Telmer, Yaron, 2001; Krebs, 2003; Barlevy, 2004). (iv) *By empirically estimating the contribution of tropical cyclones to productivity, depreciation, and income risks*, we can uses these frameworks to compare welfare and growth under current vs. future storm risk distributions.

[1] Important exceptions described below include Hsiang and Jina (2014) and Narita, Tol, and Anthoff (2009).

[2] Intuitively, this is because changes in the riskiness of production alter growth through multiple channels, including changes in household savings and investment behavior, and further affect welfare by changing the variability of consumption. Changes in observed output growth and welfare can thus be of the opposite sign if, for instance, they are driven by increased precautionary savings in the face of higher income risk.

The paper proceeds as follows. First, we formalize these ideas in the context of the stochastic endogenous growth model of Krebs (2003) and describe our application to the study of cyclone risks. Most importantly, we use the model to determine the extreme weather event impact channels that need to be empirically quantified in order to calibrate the model. These include cyclone strike impacts on total factor productivity, depreciation, and the variance of idiosyncratic income shocks facing households. The second step of the analysis considers each of these impact channels empirically. We again build on the tools developed in the macroeconomics literature to estimate the variance of idiosyncratic income shocks conditional on the state of the U.S. business cycle (e.g., Carroll and Samwick, 1997; Meghir and Pistaferri, 2004; Storesletten, Telmer, Yaron, 2004) in order to estimate the variance of income shocks *conditional on the state of cyclone activity*. Currently, our application focuses on Vietnam and uses the 2002, 2004, 2006, 2008, 2010, 2012, and 2014 waves of the Vietnamese Household Living Standards Survey (VHLSS), along with detailed historical cyclone track information from the IBTRACs. We further consider aggregate damage and production data to characterize aggregate level impacts (using EM-DAT and Penn World Tables, respectively). With these empirical quantifications in hand, we calibrate the model to enable simulation of output growth, consumption, savings, and investment behavior as a function of both the probability distribution of cyclone shocks, and in response to the realization of these shocks. Though calibrated with *weather* impact estimates, the model thus speaks to the effects of changes in the *climate* by explicitly modeling households' behavioral responses to changes in the distribution of expected weather shocks.

The third step utilizes data on simulated cyclone tracks under current (1980-2000) and future (2080-2100, IPCC emissions scenario A1b) climatic conditions from Emanuel (2008) in order to estimate changes in the probability distribution of our cyclone state variables due to global warming. Emanuel (2008) provides estimates based on four different climate models (CNRM: Gueremy et al., 2005; ECHAM: Cubasch et al., 1997; GFDLCM: Manabe et al., 1991; MIROC: Hasumi and Emori, 2004). We conduct a Monte Carlo analysis on these tracks in order to estimate changes in the probability distributions relevant to our state variables and empirical setting of Vietnam. Finally, the fourth step uses theses estimates to re-calibrate the model, and compares investment, savings, output growth, and welfare under current vs. future cyclone risks. That is, the analysis compares outcomes in two sets of steady-states: one matching the current climate, and four potential future cyclone risk distributions.[3]

We find that climate change-induced shifts in cyclone risks may have an economically significant impact on long-run growth rates in Vietnam, depressing average growth by $0.07 - 0.14$

[3] We do not model the transition between the current and the future climate for two reasons. First, we lack data on the projected interim evolution of cyclone distribution changes. Second, learning and belief updating - which are not accounted for in the present model - may play an important role and have significant effects on asset prices in the transition process (e.g., Bakkensen and Barrage, 2017b).

percentage points in the benchmark calibration. This equilibrium outcome is the result of three partly countervailing effects: (i) Households respond to higher cyclone risk by increasing savings rates, increasing growth, ceteris paribus. (ii) Investment shifts from assets with higher cyclone risk vulnerability (e.g., livestock capital) to those with lower vulnerability (e.g., human capital for salaried work), causing households to forgo some high risk/high return opportunities and lowering growth, ceteris paribus. (iii) Stronger storms adversely affect average depreciation and productivity levels, lowering growth, ceteris paribus. While the net impact estimates may seem modest, they are actually very similar in magnitude to recent estimates of the growth cost of U.S. business cycles which range from $0.07-0.40$ percentage points (Krebs, 2003; Barlevy, 2004). The associated welfare effects of these changes - measured as percentage of initial period consumption agents would be willing to forgo to avoid climate change - range from 0.85% to 12.75%.

The remainder of this paper proceeds as follows. Section 2 briefly reviews the related literature. Section 3 describes the theoretical framework and uses it to motivate the cyclone impact channels that we target for empirical estimation in Section 4. Section 5 presents the model calibration and simulation results. Finally, Section 6 concludes.

2 Literature Context

A growing literature analyzes the impacts of climate change on cyclone impacts, focusing primarily on modeling direct losses such as property damage (see meta analysis by Ranson et al., 2014). Early studies provided seminal estimates but often relied on basic statistical assumptions regarding mean increases in cyclone intensity (e.g., Nordhaus, 2010) or expert elicitation (e.g., Pielke, 2007). More recent work utilizes more detailed future cyclone simulation data (e.g., Hallegate, 2007; Emanuel, 2011; Mendelsohn et al., 2012, Hsiang and Jina, 2014). While some studies include Monte Carlo analysis to estimate the sensitivity of future losses to changes in storm intensity and other factors (Dinan, 2017), to the best of our knowledge, this literature has generally focused on changes in the mean of future cyclone counts and characteristics, without accounting for the effects of associated changes in cyclone variance on behavior or welfare.

Much of this literature has moreover focused on changes in direct losses, leaving the evaluation of associated general equilibrium and growth effects to future work. Two important prior studies advancing the literature in this direction include Narita, Tol, and Anthoff (2009) and Hsiang and Jina (2014). Narita, Tol, and Anthoff (2009) incorporate direct cyclone damages into the FUND integrated assessment model. Cyclone losses then endogenously change the trajectory of future output by decreasing investment in aggregate capital, albeit under the assumption of a fixed savings rate. Similarly, Hsiang and Jina (2014) estimate the effects of cyclone strikes on growth in a global panel regression framework, and use the resulting reduced-form impact estimates to project changes in output growth due to climate change over the 21st Century. Though pioneering in this effort, the panel fixed effects approach implicitly holds constant changes in savings and investment behavior in response to long-run cyclone *risks*, as argued by Bakkensen and Barrage (2016). That is, cyclones affect growth not only through strike's direct impacts, but also through the effect of cyclone *risk* on household savings and investment behavior in anticipation of strikes. Bakkensen and Barrage (2016) find, empirically, that the baseline growth rate of countries is positively associated with cyclone risk (in line with prior results from cross-country analyses, e.g., Skidmore and Toya, 2002), and argue that the *net* effect of cyclones on growth is significantly smaller than the effect of strikes. The *welfare* consequences of these countervailing effects remain, however, an open question. In theory, changes in cyclone risks can affect growth and welfare in opposite ways (Bakkensen and Barrage, 2016; see also the benchmark results of Krebs 2003, 2003b). Consequently, this study builds on the literature by presenting a structural endogenous growth framework that simultaneously accounts for changes in future storm strike damages and behavioral responses to changes in the cyclone risk distribution.

Our approach takes advantage of the tools developed in the macroeconomics literature on the cost of business cycles. Lucas (1987) famously set out to quantify household willingness to pay to eliminate business cycle fluctuations, and found surprisingly small effects. Specifying a utility function over consumption and taking into account the empirically observed variability in consumption in the post-War United States, he estimated that households would be willing to give up less than 0.1% of consumption each year to eliminate observed consumption fluctuations. Subsequent work explored the robustness of this result to a wide range of considerations, ranging from heterogeneous agents (e.g., Krusell and Smith, 1999) to alternative preference specifications (e.g., Obstfeld, 1994). Most relevant for our purposes, several authors noted that a change in economic risks would alter not only equilibrium consumption volatility, but potentially also long-run growth. For example, Barlevy (2004) finds that accounting for endogenous growth effects (in a stochastic AK growth model with diminishing returns to investment) increases the welfare costs of business cycles by two orders of magnitude compared to Lucas' estimates. Finally, motivated by empirical evidence on the importance of business cycles for the variability of idiosyncratic income shocks facing households, Krebs (2003) advanced the literature further through a framework with both incomplete markets *and* endogenous growth. He finds economically significant effects of business cycles on growth and welfare, and that variation in idiosyncratic risks accounts for the majority of the welfare costs. Motivated by these findings, we use Krebs' (2003) framework for our analysis, as described in the next Section.

3 Model

This section describes the benchmark model, which is essentially a re-interpretation of the stochastic endogenous growth framework with incomplete markets developed by Krebs (2003). We make some cosmetic modifications for the current setting, but no substantive changes at this stage, as Krebs' model is extremely rich and can already accommodate the first order cyclone impact channels we wish to investigate. Extensions of interest are discussed below.

The model features an economy populated by $i = 1, ..., N$ households. The exogenous state at time t can be represented by a vector of shocks $(s_{1t}, s_{2t}, ..., s_{Nt}, S_t)$ where S_t is the aggregate shock (e.g., in our setting, a category 5 hurricane landfall in Vietnam) and s_{it} are idiosyncratic shocks as they affect individual household i (e.g., flooding on its property). The shocks are assumed to be *iid* over time and across households.

The production structure of the economy features two types of capital. Krebs considers human and physical capital, and assumes that physical capital returns - though uncertain - are the same across households, whereas human capital is also subject to uninsurable idiosyncratic shocks affected by economic fluctuations. For our purposes, we consider a more general interpretation where there are two types of assets households can invest in: k_2 represents all investments that are vulnerable to cyclone strikes not only at the aggregate level, but that also through uninsurable idiosyncratic shocks affecting households differentially. For example, our empirical results indicate that income from animal husbandry is subject to permanent idiosyncratic shocks from cyclones. This result makes sense if storms destroy productive assets in this sector, such as by killing animals, damaging enclosures and equipment, etc. In contrast, k_1 represents investments which - though vulnerable to cyclone strikes in the aggregate - do not additionally entail uninsurable idiosyncratic risk. For example, in our empirical setting, financial capital as well as human capital used for salaried labor appear to fall into this category. It should be noted that this category can include income-generating assets that are vulnerable to idiosyncratic cyclone shocks as long as those risks are insurable (e.g., tourism infrastructure), leaving investors with no *residual* idiosyncratic risk. While we will ultimately let the data tell us which assets fall into which category, the model description will refer to k_2 and k_1 as generic aggregates.

The representative household in region i thus maximizes his expected lifetime utility by choosing state-contingent plans for consumption c_{it} and his investments in capital of each type (x_{1it}, x_{2it}) by solving:

$$\max E_0 \sum_{t=0}^{\infty} \beta^t U(c_{it}) \tag{1}$$

subject to constraints:

$$\begin{aligned}
c_{it} + x_{1it} + x_{2it} &= k_{1it}R_{1t} + k_{2it}R_{2t} \\
k_{1it+1} &= (1-\delta_{1t})k_{1it} + x_{1it} \\
k_{2it+1} &= (1-\delta_{2t}-\eta_{it})k_{2it} + x_{2it} \\
& \quad k_{1i0}, k_{2i0} \text{ given}
\end{aligned}$$

Here k_{1it} and k_{2it} denote household $i's$ holdings of each type of capital at the beginning of period t, R_{1t} and R_{2t} are the gross returns for each asset category, δ_{jt} is the depreciation rate of capital type j at time t, and η_{it} denotes the idiosyncratic shock to k_{2it} returns for household i at time t. The average depreciation rate of each type of capital depends on the aggregate shock $\delta_{1t} = \delta_1(S_t)$, $\delta_{2t} = \delta_2(S_t)$. Intuitively, if average depreciation increases with a hurricane landfall, this can be captured in δ_{2t} whereas the η_{it} terms then represent *relative* departures from average depreciation at the household level. Consequently, we can retain Krebs' assumption that $E[\eta_{it}|S_t] = 0$. Note that these shocks are defined as a function $\eta : s \times S \to R$ and assign each (s, S) a realization $\eta_{it} = \eta(s_{it}, S_t)$. Section 4 empirically estimates how the dispersion of these shocks varies with the aggregate cyclone state S_t in order to calibrate this relationship. Finally, the aggregate gross returns R_{1t} and R_{2t} also vary with cyclone activity through the dependence of total factor productivity A_t on the cyclone state: $A_t = A(S_t)$.

The market and production structure in Krebs' (2003) framework can be interpreted in one of two ways: One, as a competitive market economy where a representative firm rents factors in national markets, maximizing expected profits:

$$\max_{K_{1t}, K_{2t}} (A_t K_{1t}^{\alpha} K_{2t}^{1-\alpha}) - R_{1t}K_{1t} - R_{2t}K_{2t}$$

where K_{jt} denotes the aggregate capital stock of type j $(\sum_i k_{jit})$. Two, as a autarkic economy where each household produces and consumes in isolation with production technology $A_t k_{1it}^{\alpha} k_{2it}^{1-\alpha}$, maximizing (1) subject to:

$$\begin{aligned}
c_{it} + x_{1it} + x_{2it} &= A_t k_{1it}^{\alpha} k_{2it}^{1-\alpha} \\
k_{1it+1} &= (1-\delta_{1t})k_{1it} + x_{1it} \\
k_{2it+1} &= (1-\delta_{2t}-\eta_{it})k_{2it} + x_{2it} \\
& \quad k_{1i0}, k_{2i0} \text{ given}
\end{aligned}$$

Krebs (2003) formally shows that the stationary recursive equilibrium allocations of the autarkic and competitive market economies coincide in this setting. This insight is valuable for our application as one may question the empirical validity of the assumption that households rent factors in national markets in a developing economy with significant rural production. The benchmark model thus nests the two extreme cases of competitive national markets and autarkic production. In ongoing work we are further exploring an extension to the framework of Bakkensen and Barrage (2016), which considers a mixed case where strictly local entrepreneurial production subject to idiosyncratic storm shocks is added to the Krebs (2003b, 2006) frameworks with a national formal sector.

Define the household's wealth at time t as $w_{it} \equiv k_{1it} + k_{2it}$, and let $\widetilde{k}_{it} \equiv \frac{k_{1it}}{k_{2it}}$ denote his capital-type ratio. In a stationary equilibrium, this ratio is constant and equal across households, so that $\widetilde{k}_{it} = \widetilde{K}_t \equiv \frac{K_{1t}}{K_{2t}} = \widetilde{K} = \widetilde{k}$. The stationary equilibrium aggregate returns to each factor are then given by the profit-maximizing conditions:

$$\begin{aligned} R_{1t} &= R_1(\widetilde{k}, S_t) = (\alpha) A(S_t)(\widetilde{k})^{\alpha-1} \\ R_{2t} &= R_2(\widetilde{k}, S_t) = (1-\alpha) A(S_t)(\widetilde{k})^{\alpha} \end{aligned} \tag{2}$$

Further define the average *net* returns as:

$$\begin{aligned} r_{1t}(\widetilde{k}, S_t) &= R_1(\widetilde{k}, S_t) - \delta_1(S_t) \\ r_{2t}(\widetilde{k}, S_t) &= R_2(\widetilde{k}, S_t) - \delta_2(S_t) \end{aligned}$$

The household's realized return on his portfolio at time t is thus given by a weighted share of the net returns to each of his assets:

$$r(\widetilde{k}_{it}, s_{it}, S_t) = \left(\frac{\widetilde{k}_{it}}{1+\widetilde{k}_{it}}\right) r_{1t}(\widetilde{k}, S_t) + \left(\frac{1}{1+\widetilde{k}_{it}}\right) [r_{2t}(\widetilde{k}, S_t) + \eta(s_{it}, S_t)]$$

Finally, let $\widetilde{c} \equiv \frac{c_{it}}{w_{it}(1+r(\widetilde{k}_{it}, s_{it}, S_t))}$ denote the household's consumption-out-of-wealth ratio, and assume that the household's preferences are given by:

$$u(c_{it}) = \frac{c_{it}^{1-\gamma}}{1-\gamma}$$

It is then straightforward to show that the capital ratio $\widetilde{k}$ and the savings rate $(1-\widetilde{c})$ that solve the household's problem are jointly determined by the following conditions:

$$\widetilde{c} = 1 - \{\beta E[(1 + r(\widetilde{k}, s_i, S))^{1-\gamma}]\}^{\frac{1}{\gamma}} \tag{3}$$

$$0 = \beta E\left[\frac{r_2(\widetilde{k}, S) + \eta(s_i, S) - r_1(\widetilde{k}, S)}{(1 + r(\widetilde{k}, s_i, S))^{\gamma}}\right] \tag{4}$$

Intuitively, (3) follows from the household's Euler equation with the budget constraint ($w_i' = (1 + r(\widetilde{k}, s_i, S))w_i - c_i$) and the definition of $\widetilde{c}$ ($c_i' = \widetilde{c}(1 + r(\widetilde{k}', s_i', S'))w'$) substituted in. In turn, (4) represents a no-arbitrage condition based on the expected excess return for investments in type 2 assets. Note that the expectation is taken over both aggregate and idiosyncratic risk. Equations (3)-(4) thus implicitly characterize how cyclone risk affects equilibrium savings and investment patterns $\widetilde{c}$, $\widetilde{k}$, which, in turn, determine both individual and aggregate growth. In particular, individual consumption growth in each state of the world g_{it+1} is given by:

$$g_{it+1} = g(\widetilde{k}, s_{it+1}, S_{t+1}) \equiv \frac{c_{it+1}}{c_i} = (1 - \widetilde{c})[1 + r(\widetilde{k}, s_{it+1}, S_{t+1})] \tag{5}$$

Aggregate consumption growth, by the law of large numbers, is given by:

$$\frac{C_{t+1}}{C_t} = E\left[\frac{c_{it+1}}{c_i}\right] = (1 - \widetilde{c})(1 + E[r(\widetilde{k}, s_{it+1}, S_{t+1})]) \tag{6}$$

Finally, Krebs shows that expected lifetime utility is then given by:

$$E_0\left[\sum_{t=0}^{\infty}\beta^t \frac{c_{it}^{1-\gamma}}{1-\gamma}\right] = \frac{c_{i0}^{1-\gamma}}{(1-\gamma)(1 - \beta E[1 + g(\widetilde{k}, s_i, S)^{1-\gamma}])}, \gamma \neq 1 \tag{7}$$

$$E_0\left[\sum_{t=0}^{\infty}\beta^t \log(c_{it})\right] = \frac{1}{1-\beta}\log c_{i0} + \frac{\beta}{(1-\beta)^2}E[\log(1 + g(\widetilde{k}, s_i, S))] \tag{8}$$

A change in the cyclone risk distribution is thus predicted to affect households' lifetime utility through its effects on (i) the allocation of capital across sectors $\widetilde{k}$, (ii) the savings rate $(1-\widetilde{c})$, (iii) the expected consumption growth rate $g(\widetilde{k}, s_i, S)$, and, depending on one's assumptions about the timing of the risk change, initial consumption levels $c_{i0} = \widetilde{c}[1 + r(\widetilde{k}_{i0}, s_{i0}, S_0)]w_{i0}$. In order to quantify these effects, we proceed to empirically explore the cyclone impact channels underlying these equilibrium outcomes. Table 3 summarizes these impact channels and the data we will use to explore them in Section 4.

Table 3 : Cyclone Impact Channels		
Impact	Description	Empirical Estimation
$\sigma_\eta^2(S_t)$	Idiosyncratic income shock variance conditional on S_t	Panel household surveys (VHLSS) Historical cyclone tracks (IBTrACS)
$\delta_{k2}(S_t)$, $\delta_{k1}(S_t)$	Avg. capital depreciation in each cyclone state S_t	Direct losses (EM-DAT), capital stocks (PWT) Historical cyclone tracks (IBTrACS)
$A(S_t)$	Aggregate productivity by cyclone state S_t	Aggregate factor inputs and output (PWT) Household surveys (VHLSS), Cyclones (IBTrACS)
$\pi_{2000}(S_t)$, $\pi_{2100}(S_t)$	Current vs. future probability distribution of cyclone states S_t	Historical cyclone tracks (IBTrACS) Simulated cyclone tracks (Emanuel, 2008)

In sum, the model provides a set of specific cyclone impact channels that determine the effects of cyclone risk on growth and welfare in general equilibrium. Importantly, the model thus provides the critical link between empirical estimates of the impacts of *weather* realizations and predictions of the effects of a change in the *climate*. As is well-noted in the empirical literature, one of the most fundamental concerns in drawing inference on climate change impacts form weather studies is that households will adapt to changes in the long-run moments of the weather distribution (see, e.g., Mendelsohn, Nordhaus, and Shaw, 1994; Dell, Jones, Olken, 2014; Hsiang, 2016). Our framework addresses this concern by explicitly modeling adaptation as a function of the estimated costs of weather realizations. For example, if the risk of a high cyclone realization increases with climate change, households will shift their investments to assets less at risk from cyclone strikes (i.e., a change in $\widetilde{k}$), and may also change their overall savings rate to cope with higher overall risk (i.e., a change in $\widetilde{c}$). Of course, the extent to which households adapt depends on the downside risks they face from bad weather events, which is the focus of the next Section.[4]

[4] One critical caveat is that the analysis currently does not allow for adaptation on the intensive margin. That is, while households can shift the types of income-generating assets they invest in, they cannot currently alter the extent to which a given asset is affected by storms. That is, in the model households take $\delta_{k1}(S_t)$ as given, whereas, in reality, infrastructure can be built differently to reduce damages for a given cyclone state S_t.

4 Empirical Estimation

4.1 Conditional Income Variance

Our first empirical objective is to quantify the contribution of cyclone strikes to idiosyncratic income risks faced by households. More formally, we seek to estimate the conditional variance of income shocks, conditioning on the cyclone state S_t. Our estimation builds on a literature that has developed tools to estimate the variance of income shocks both unconditionally (e.g., Carroll and Samwick, 1997) and conditional on the business cycle (e.g., Costas and Meghir, 2004; Storesletten, Telmer, and Yaron, "STY" 2004).

First, following STY, we focus on y_{ijt}^h, the logarithm of type j earnings (e.g., labor income) for household i of age h at time t. Suppressing the j subscripts for legibility, y_{it}^h is modeled as:

$$y_{it}^h = g(x_{it}^h, m_t) + u_{it}^h$$

where x_{it}^h are deterministic and observable determinants of households' earnings (e.g., age, gender composition, etc.), m_t are aggregate time effects, and the u_{it}^h are idiosyncratic earnings shocks to the household. These shocks, in turn, may include a temporary shock ε_{it} (which also includes measurement error), and a permanent component z_{it}^h :

$$u_{it}^h = z_{i,t}^h + \varepsilon_{it} \tag{9}$$

The permanent component follows a random walk:

$$z_{i,t}^h = z_{i,t-1}^h + \eta_{it} \tag{10}$$

We further follow STY in assuming that $\varepsilon_{it} \sim Niid(0, \sigma_\varepsilon^2)$ and $\eta_{it} \sim Niid(0, \sigma_\eta^2(S_t))$, where S_t denotes the aggregate "cyclone state" of the economy at time t. In principle, one could consider a range of cyclone state measures S_t: a binary variable for whether a cyclone made landfall in period t, the maximum Saffir-Simpson category amongst storms making landfall in period t, discretized measures of maximum wind speed, minimum pressure, etc. In the literature, STY focus on a regime-switching conditional variance that takes on one of two values depending on whether the economy is in an aggregate expansion (above-average GDP growth) or contraction (below-average growth). We thus begin by exploring analogous binary cyclone state measures as described below, but note that extensions to more nuanced state spaces are in progress. The regime-switching model adopts a threshold value $\overline{S}$ for each cyclone activity measure (e.g., dissipated energy), and classifies each year as 'high' cyclone state if observed $S_t > \overline{S}$, and as 'low' otherwise. More formally, we then seek to estimate the conditional variance:

$$\sigma^2_\eta(S_t) = \begin{cases} \sigma^2_H & \text{If } S_t > \overline{S} \\ \sigma^2_L & \text{If } S_t < \overline{S} \end{cases} \tag{11}$$

For illustrative purposes, we also show some results for a linear-continuous specification:

$$\sigma^2_\eta(S_t) = \sigma^2_{\eta 0} + \gamma \cdot S_t \tag{12}$$

The estimation then proceeds as follows. First, we isolate the unexplained component of incomes by regressing y^h_{it} on:

$$g(x^h_{it}, m_t) = \beta_0 + x^{h\prime}_{it}\boldsymbol{\beta} + \delta m_t \tag{13}$$

where x^h_{it} includes controls for household size, share of male members, mean and household head's education, mean and household head's age, and head's age squared. The results are shown in Appendix Table A1 by our final income categorization (i.e., y^h_{i2t} and y^h_{i1t}), described below. Next, we note the following property implied by (9) and (10):

$$\begin{aligned} u^h_{it} &= z^h_{i,t} + \varepsilon_{it} \\ &= \sum_{j=0}^{h-1} \eta_{i,t-j} + z^0_{i,t-h} + \varepsilon_{it} \end{aligned} \tag{14}$$

Intuitively, $\sum_{j=0}^{h-1} \eta_{i,t-j}$ denotes household $i's$ lifetime history of exposure to shocks $\eta_{i,t-j}$, and $z^0_{i,t-h}$ is the household's initial shock. At this juncture, the literature differs in how authors proceed and address the initial conditions problem. With sufficiently rich panel data, such as with the U.S. Panel of Income Dynamics (PSID), it is possible to use within-household variation in income shocks over time to difference out $z^0_{i,t-h}$ (Carroll and Samwick, 1997; Costas and Meghir, 2004). Alternatively, STY assume that $z^0_{i,t-h} = 0$ and focus on cross-sectional variation in u^h_{it} across households of a given age group in each year. We consider each approach in turn.

Within-Household Variation With panel data, the $d-$period difference in idiosyncratic income components (14) is given by:

$$\upsilon^i_{t,t+d} \equiv u^{h+d}_{i,t+d} - u^h_{i,t} = \sum_{j=0}^{d-1} \eta_{i,t+d-j} + \varepsilon_{it+d} - \varepsilon_{it}$$

Given our assumptions, it is straightforward to show that:

$$Var(\upsilon^i_{t,t+d}) = E[(\upsilon^i_{t,t+d})^2] = \sum_{j=0}^{d-1} \sigma^2_\eta(S_{t+d-j}) + 2\sigma^2_\varepsilon \tag{15}$$

For the regime-switching (11) and linear (12) specifications, respectively, (15) becomes:

$$Var(\upsilon^i_{t,t+d}) = \sum_{j=0}^{d-1}[(I^H_{t+d-j})\sigma^2_H + (1 - I^H_{t+d-j})\sigma^2_L] + 2\sigma^2_\varepsilon \tag{16}$$

$$Var(\upsilon^i_{t,t+d}) = d \cdot \sigma^2_{\eta 0} + \sum_{j=0}^{d-1}(S_{t+d-j}) + 2\sigma^2_\varepsilon \tag{17}$$

Here, I^H_{t+d-j} is an indicator variable for whether the economy was in a high cyclone state in period $t + d - j$. Equations (16) and (17) thus define our first set of estimating equations based on the panel households available in the VHLSS.

Cross-Sectional Variation Given the limited temporal dimension of household panel data even in the PSID, Storesletten, Telmer, and Yaron (2004) propose an alternative approach based on the *cross-sectional variance* in u^h_{it}, denoted $\widetilde{Var}(u^h_{it})$. One of STY's fundamental insights is that one can compare cohorts at a given age but with different lifetime exposures to shocks in order to draw inference on the effect of these shocks on the variance in incomes. For example, 30-year old workers in 2004 have experienced a different cyclone shock history compared to 30-year old workers in 2014.[5] If the former cohort experienced more high cyclone activity years than the latter, we can study to what extent this difference in histories affects the cross-sectional variance in idiosyncratic income components (taken across members of each age group in each survey year). An essential advantage of this approach is that it enables us to take advantage of the fact that weather data are available going back considerably further back in time than our survey data. That is, given that wind speeds for cyclones in the Western Pacific have been reliably recorded since 1978, we can compute detailed household working life cyclone exposure metrics starting with cohorts born in 1963, assuming that agents start their working life at age 15.[6] More formally, given STY's assumption that $z^0_{it} = 0$, and going back to (14), it is straightforward to

[5] Note again that we focus here on variation in incomes not already explained by observables and aggregate trends and fluctuations that would also differ between these cohorts.

[6] In the U.S. context, STY define $h = 1$ for 23-year old workers. However, in Vietnam, a younger age is clearly appropriate. We adopt a standard value of 15 (where, e.g., the International Labor Organization begins tracking youth employment). It should also be noted that, in the neighboring Philippines' Cebu Longitudinal Health and Nutrition Survey (Carolina Population Center, UNC Chapel Hill), the average age when mothers acros the 1991-2005 survey waves reported that they had started to work is 15.6 years. The focus on cohorts born after 1963 also helps mitigate concerns about Vietnam War effects on older generations.

show that:

$$\widetilde{Var}(u_{it}^h) = \sigma_\varepsilon^2 + \sum_{j=0}^{h-1} \sigma_\eta^2(S_{t-j}) \tag{18}$$

For the regime-switching and linear structures on $\sigma_\eta^2(S_t)$, respectively, (18) becomes:

$$\widetilde{Var}(u_{it}^h) = \sigma_\varepsilon^2 + \sum_{j=0}^{h-1} [(I_{t-j}^H)\sigma_H^2 + (1 - I_{t-j}^H)\sigma_L^2] \tag{19}$$

$$\widetilde{Var}(u_{it}^h) = \sigma_\varepsilon^2 + \sigma_{\eta,0}^2 \cdot h + \gamma \cdot \sum^{h-1} S \tag{20}$$

4.2 Data

Households and Income: This section uses the Vietnamese Household Living Standards Survey (VHLSS) survey waves of 2004, 2006, 2008, 2010, 2012, and 2014 to estimate (16)-(17) and (19)-(20). The VHLSS is a nationally representative survey that has been administered by the Vietnamese General Statistics Office every two years since 2002. A subset of households are given a more detailed survey on income and expenditures, which is the focus of our analysis. Half of households are re-sampled the following wave (depending on the year), and another half are sampled for a third time the following wave, providing the necessary panel variation to estimate (16)-(17). The initial sample consists of all 55,763 household-survey observations from 39,157 unique households covered in the 2004-2014 survey waves. Of these, we cut 30,484 observations stemming from household-survey years with household heads born before 1962. Following Carroll and Samwick (1997), we further exclude households whose income in any year is less than 20% of the household's average over the panel, affecting 46 observations. Finally, we exclude the 30 most extreme income outliers whose total reported income exceeded the sample mean by more than 10 standard deviations.

We aggregate incomes at the household-year level, initially in the following categories:

Label	Description
Labor	Labor (wage) income + benefits
Crops	Household's cultivation of crops
LiveHunt	Animal husbandry, hunting, trapping
AgServ	Agricultural services (ploughing, pest control, etc.)
Fore	Forestry (planting/harvesting/collecting products from trees)
Aquac	Aquaculture and fishing
Entrep	'Activities of your own production and business' (Non-ag, non-livestock, etc.)
FinTran	Financial (interest, rents, etc.) + transfers (remittances, social benefits, insurance)

Finally, all financial variables are converted to 2010VND using U.S. Federal Reserve (FRED) data on the Vietnamese CPI.

Cyclones We obtain storm data from the International Best Track Archive for Climate Stewardship (IBTrACS), which provides individual cyclone track information including wind speeds, minimum sea level pressure, latitude, and longitude. We process the data to generate the following cyclone state variables for Vietnam:

$\mathbf{S_t}$ Measure	Description
Count_t	Annual landfall count of tropical storms
CyCount_t	Annual landfall count of tropical cyclones (i.e., Saffir-Simpson Category 1+)
Energy_t	Annual sum across storms' (maximum windspeeds)^3
$\overline{S}$ Measure:	
$\overline{\text{Count}_{1978-2015}}$	Average tropical storm landfall count (1978-2015)
$\overline{\text{CyCount}_{1978-2015}}$	Average tropical cyclone landfall count (1978-2015)
$\overline{\text{Energy}_{1978-2015}}$	Average dissipated energy (1978-2015)
$P_{75}(\text{Energy}_{1978-2015})$	75^{th} percentile of dissipated energy (1978-2015)

4.3 Results

The results are presented in two parts. First, we describe conditional variance results for all income categories. Motivated by these results, we then offer a classification of income sources into Y_1 and Y_2, and present the main estimation for the calibration of the model.

To begin, Figure 1 provides suggestive evidence from scatter plots of the cross-sectional variance of income shocks by age cohort and survey year, plotted against each cohort's working life cyclone exposure (measured as $\sum_{j=0}^{h-1} \text{CyCount}_j$). Some climate-sensitive income sources, such as crops and livestock/hunting, appear to exhibit a positive association between cohort cyclone exposures and income shock variance. On the other hand, financial, labor, and entrepreneurial income fail to visually exhibit cyclone state heteroskedasticity in this graph. Of course, cohort cyclone exposure is also strongly correlated with age, which may increase income variability through accumulated non-cyclone shocks as well. Nonetheless, the patterns appear to differ between intuitively cyclone-vulnerable activities, such as farming, compared to alternative income sources, such as salaried labor.

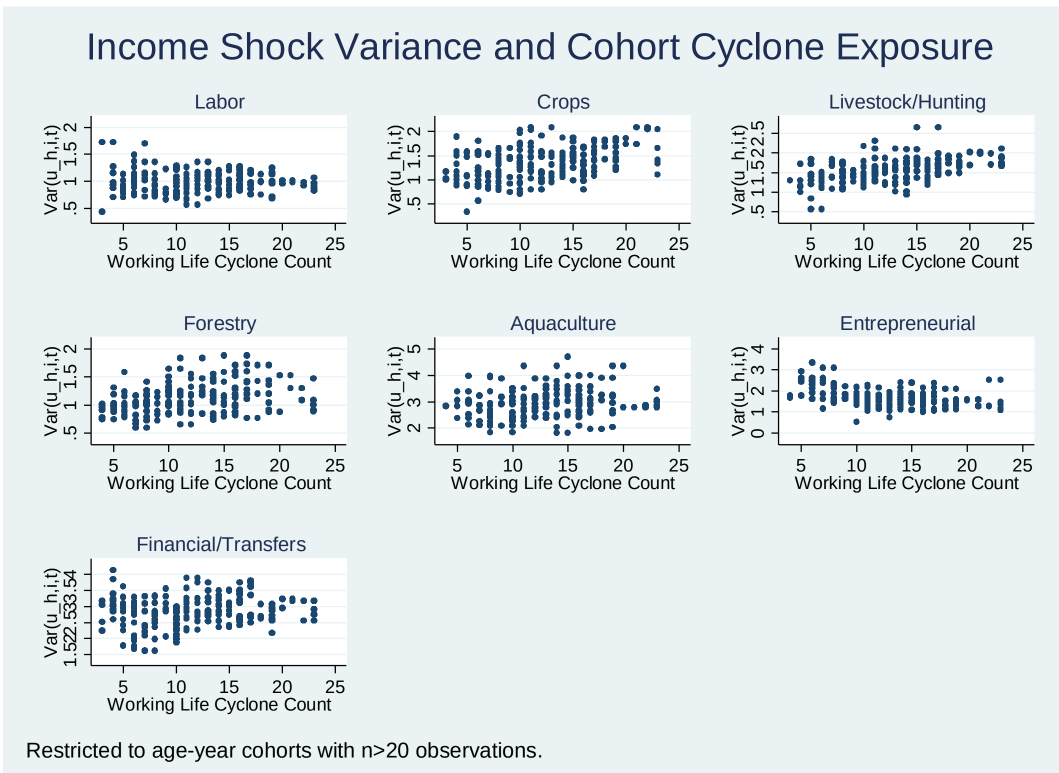


Figure 1

Tables 2 presents the within-household results for the regime-switching specification with $S_t = \text{CyCount}_t$. As the annual average $\overline{S}$ is less than unity Vietnam, this state variable effectively measures whether at least one proper cyclone (Category 1+) made landfall in a given year.

Table 2: Within-Household Estimates of Conditional Income Shock Variances							
	Labor	Crops	Livestock	Forestry	Aquac.	Entrep.	Financial/Transfr.
$\widehat{\sigma_H^2}$	0.036	0.069**	0.178***	0.055	0.016	0.066	0.021
	(0.030)	(0.030)	(0.065)	(0.043)	(0.106)	(0.060)	(0.096)
$\widehat{\sigma_L^2}$	0.012	0.048	0.168**	0.017	0.048	0.144**	0.253**
	(0.035)	(0.036)	(0.066)	(0.048)	(0.120)	(0.072)	(0.117)
$\widehat{\sigma_\varepsilon^2}$	0.274***	0.267***	0.529***	0.390***	0.671***	0.300***	1.851***
	(0.039)	(0.037)	(0.068)	(0.051)	(0.125)	(0.072)	(0.125)
Obs.	3,111	3,600	2,516	1,421	870	1,618	4,930
Adj. R^2	0.160	0.128	0.249	0.230	0.211	0.167	0.268

Table presents results of OLS regression of squared difference of individual households' residuals from income regressions (13) for each income source indicated in table columns on the household's years of working life in 'high' cyclone state (one or more Cat. 1+ cyclone landfalls), years in 'low' cyclone state (tropical storms or less), and the number 2 (constant omitted). S.E.'s clustered at HH level (*** p$<$0.01, ** p$<$0.05, * p$<$0.1).

The results suggest that cyclone strikes can increase the variance of idiosyncratic income shocks facing households, particularly for environmentally sensitive activities such as agriculture and animal husbandry. The significantly higher variance of financial income during low cyclone states may, in contrast, be due to the inclusion of remittances, insurance, and social assistance payments in this income category, which would insure the household at least partially against cyclone shocks.[7] In order to align the data with the theoretical model, we propose the following benchmark categorization of income-generating activities that are (Y_2) and are not (Y_1) subject to idiosyncratic income risks from storms (above and beyond the aggregate productivity and depreciation risks that can affect both Y_1 and Y_2):

$$\begin{aligned} &[Y_2] \text{ Crops, Livestock, Forestry, Aquaculture, Ag. Services} \\ &[Y_1] \text{ Labor, Entrepreneurial, Financial/Transfers} \end{aligned} \tag{21}$$

Table 3 showcases the within-household estimation results (analogous to Table 2) for the newly aggregated income categories across three measures for the 'high' cyclone state: above-average cyclone strikes, above-average energy dissipation, and above-75$^{\text{th}}$ percentile energy dissipation. The finding that the variance of idiosyncratic income shocks increases with cyclone activity

[7] We hope to test this hypothesis formally going forward by utilizing both additional data on disasters available in the VHSS at the commune level, and through decompositions of financial and entrepreneurial income to the extent available in the relevant survey waves.

$(\widehat{\sigma_H^2} > \widehat{\sigma_L^2})$ appears robust across specifications.

Table 3: Within-Household Estimates of Conditional Income Shock Variances: Y_2

S_t Measure:	$\text{CyCount}_t > \overline{\text{CyCount}_{1978-2015}}$	$\text{Energy}_t > \overline{\text{Energy}_{1978-2015}}$	$\text{Energy}_t > P_{75}(\text{Energy}_{1978-2015})$
$\widehat{\sigma_H^2}$	0.117***	0.113*	0.107*
	(0.038)	(0.059)	(0.055)
$\widehat{\sigma_L^2}$	0.070*	0.060	0.043
	(0.041)	(0.050)	(0.043)
$\widehat{\sigma_\varepsilon^2}$	0.272***	0.300***	0.324***
	(0.045)	(0.060)	(0.053)
Obs.	3,956	3,956	3,956
Adj. R^2	0.120	0.119	0.119

Table presents results of OLS regression of squared difference of individual households' residuals from income regressions (13) for Y_2 on the household's years of working life in 'high' cyclone state as per indicated S_t measure, years in 'low' cyclone state, and the number 2 (constant omitted). S.E.'s clustered at HH level (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Next, Figure 2 displays scatter plots of the cross-sectional variance of income shocks for each age-year group against measures of their working lifetime cyclone exposure. For these main specifications, we collapse ages into two-year bins in order to increase the underlying number of observations per variance estimate. While STY use three-year age bins, the more limited nature of our data (only six survey waves in two-year intervals) prevents us from doing so. The scatter plots are consistent with the notion that the Y_2 income shock variance is positively related to cyclone activity. However, as lifetime cyclone exposure is strongly correlated with age, caution is again warranted in interpreting these figures.

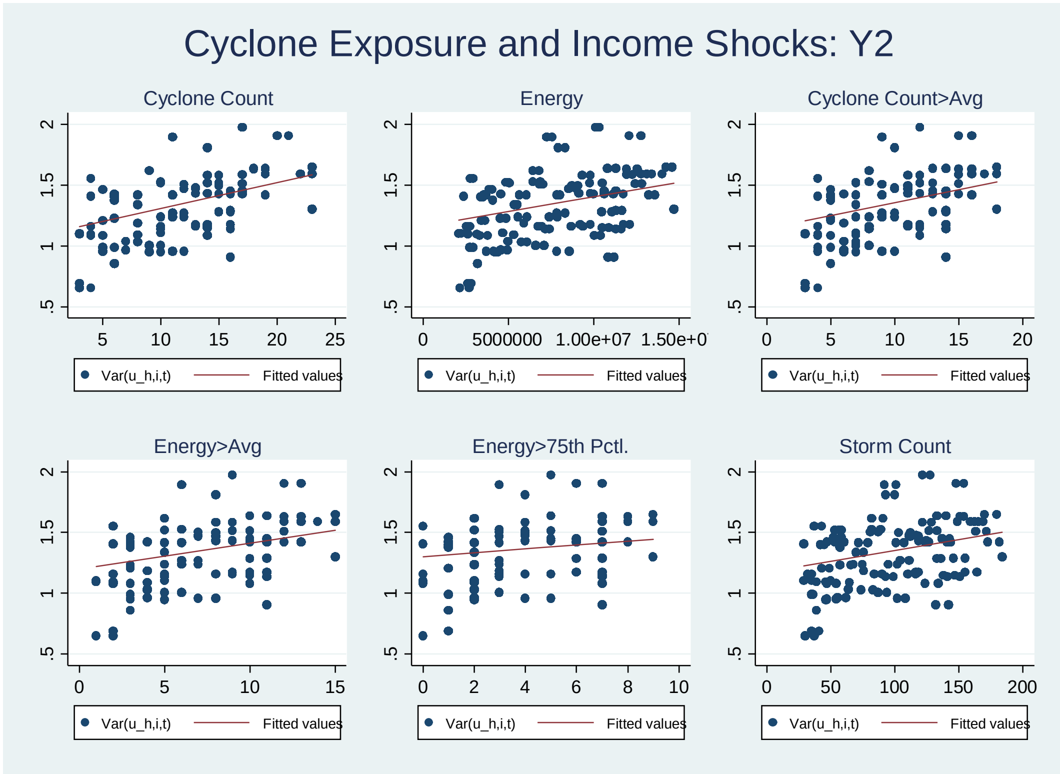


Figure 2

In order to control for the direct effects of cohort age on income dispersion, Table 4 presents results for the cross-cohort estimation (20). Unfortunately, controlling for cohort age leaves limited variation in cyclone exposure across survey waves, yielding mostly imprecise estimates.

Table 4: Cross-Sectional Income Shock Variance Regressions: Y_2

	(1)	(2)	(3)	(4)
Age bin (h)	0.020	0.064**	0.065***	0.101***
	(0.024)	(0.029)	(0.024)	(0.018)
$\sum_{j=0}^{h-1} \text{CyCount}_j$	0.013			
	(0.016)			
$\sum_{j=0}^{h-1} I(\text{CyCount}_j > \text{avg.})$		-0.024		
		(0.025)		
$\sum_{j=0}^{h-1} I(\text{Energy}_j > \text{avg.})$			-0.028	
			(0.023)	
$\sum_{j=0}^{h-1} I(\text{Energy}_j > 75^{\text{th}} \text{ Pctl.})$				-0.096***
				(0.026)
Constant	0.960***	0.867***	0.825***	0.613***
	(0.100)	(0.104)	(0.117)	(0.115)
Obs.	71	71	71	71
Adj. R^2	0.238	0.240	0.247	0.361

Table presents OLS regression results for cross-sectional variance of squared residuals from income regressions (13) for Y_2 across age-year cohorts on cohort age (2-year bins) and the indicated working lifetime cyclone exposure measures. Restricted to age-year cohorts with n>20 observations. Standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Three of the point estimates on lifetime cyclone measures are *negative,* including a significant coefficient on years with energy dissipation above the 75^{th} percentile. This result would imply a lower income shock variance during high cyclone activity, in contrast to the within-household results presented above. For example, the estimates of Column (4) would imply $\widehat{\sigma_L^2} = 0.101$ and $\widehat{\sigma_H^2} = 0.101\text{-}0.096 = 0.005$. However, Figure 3 presents a scatter plot of the residuals from a regression of the cross-sectional income shock variance on age against this measure of cohort cyclone exposure. While the best-fit line is negative, overall the pattern appears quite noisy.

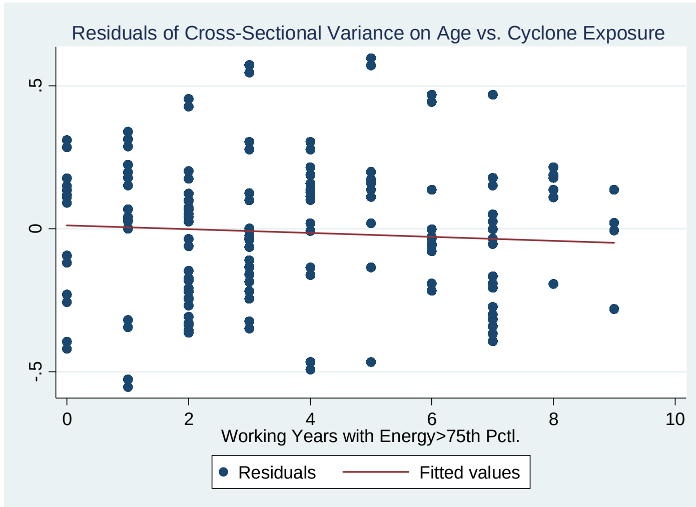


Figure 3

To summarize, the results of this section suggest that cyclone activity increases the variance of idiosyncratic income shocks for certain types of activities, such as agriculture and animal husbandry. Aggregating income across these activities (agriculture, livestock/hunting, aquaculture, forestry) and utilizing within-household variation in income shocks over time, we find that the variance of these shocks to be positively and significantly increasing in cyclone activity (Table 3). In contrast, results based on the cross-sectional variation in income shocks across age-year cohorts fails to show such an association, and suggests - if anything - a negative relationship. However, the cross-sectional estimates are generally noisy due to the limited variation in cyclone exposure across age-year cohorts compared to the cross-sectional income shock variation. Consequently, we consider the within-household results (Table 3) as the preferred specification, but note that the model calibration can incorporate and compare the implications of each of the different estimates.

4.4 Aggregate Depreciation

Tropical storms have the capacity to destroy capital. While these direct impacts are arguably the most researched and best-understood in the literature, the model calibration requires a very specific impact estimate: the depreciation rate of capital in Vietnam as a function of each cyclone state measure S_t. For example, we need an estimate of the aggregate capital depreciation rate both for years where Vietnam experiences storm energy below average $\delta(S_t = 0)$ or above average $\delta(S_t = 1)$. Unfortunately, the VHLSS survey data are neither sufficiently detailed nor frequent to permit inference on household-level capital depreciation from storms. We therefore proceed at the aggregate level.[8]

First, we obtain EM-DATA data on total direct damages caused by cyclones in Vietnam from 1990-2015. EM-DAT is a global database on disasters and their impacts maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the Université catholique de Louvain in Belgium. EM-DAT is widely utilized among academic scholars (e.g., Noy, 2009; Narita, Tol, and Anthoff, 2009, etc.) and is arguably the best publicly available source of global disaster damages, covering more than 21,00 natural and technological disasters from 1900 to the present day. A "disaster" is defined and included in the database if it meets at least one of the following criteria: 10 or more people have been killed, 100 or more people affected, a state of emergency has been declared, and/or a call for international assistance has been issued (Guha-Sapir, Below, and Hoyois, 2017). The data are compiled and cross-validated from multiple sources, including U.N. agencies, governments, insurance companies, research institutes, press agencies, and the International Federation of Red Cross and Red Crescent Societies. In spite of known concerns about issues such as missing data and measurement error (Gall, Borden, and Cutter, 2009), we thus utilize EM-DAT data for our benchmark calibration, and formally evaluate the robustness of the results through a sensitivity analysis.[9]

Second, we obtain capital stock level estimates for Vietnam from the Penn World Tables. We then approximate the fraction of aggregate capital destroyed by storms each year as the total recorded damages divided by the capital stock. Third, we examine how this damage fraction changes with cyclone activity. Figure 4 displays the time series of this fraction against both the continuous and binary state measures of cyclone energy in each year. Clearly, destruction increases with cyclone strength. Table 6 presents formal regression estimates of this relationship for several cyclone strength measures. Given the nature of the dependent variable, we consider both a fractional logit framework and present OLS estimates for comparison.

---

8 Another implication of this data limitation is that we only obtain an overall depreciation rate estimate $\widehat{\delta}(S_t)$, rather than differentiated estimates for $\delta_{k1}(S_t)$ and $\delta_{k2}(S_t)$. As one could speculate on resulting bias in either direction, differentiated values can be considered through sensitivity analysis.

9 While some scholars prefer data from private insurers such as Munich Re and Swiss Re, these agencies should have a comparative advantage only in the collection of insured losses data, which represent only a small fraction of total damages, especially in developing countries. In a direct comparison of the three leading disaster database entries (Munich Re, Swiss Re, and EM-DAT) across four countries including Vietnam, 59% of damages record magnitudes directly matched across the three datasets (Guha-Sapir and Below, 2002).

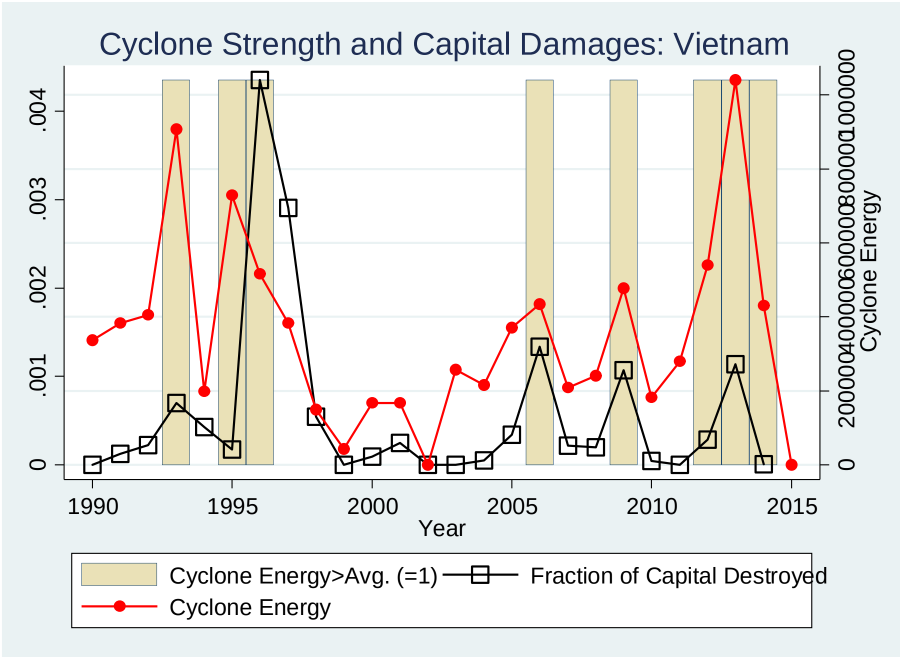

Cyclone Strength and Capital Damages: Vietnam
0
.001
.002
.003
.004
0
200000
400000
600000
800000
1000000
Cyclone Energy
1990
1995
2000
2005
2010
2015
Year
Cyclone Energy>Avg. (=1)
Fraction of Capital Destroyed
Cyclone Energy

Figure 4

Table 6: Capital Destruction and Cyclone Strikes

Dependent Variable: Fraction of Aggregate Capital Stock Destroyed

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Energy_t	9.22e-10**	1.51e-09***						
	(3.60e-10)	(4.42e-10)						
Energy_t >avg.			0.000815	0.00113***				
			(0.000497)	(0.000344)				
CyCount_t					0.000205**	0.000514**		
					(0.000101)	(0.000210)		
CyCount_t >avg.							0.000521	0.000871***
							(0.000416)	(0.000306)
Specification:	F.Logit	OLS	F.Logit	OLS	F.Logit	OLS	F.Logit	OLS
Observations	25	25	25	25	25	25	25	25
R-squared		0.326		0.311		0.200		0.253

Table presents results for fractional logit (odd columns) and OLS (even columns) regressions of the fraction of aggregate capital stock destroyed by storms in Vietnam in year t on cyclone measures: Energy_t is the cube of cumulative wind speeds in t; Energy_t >avg. is an indicator for whether energy in year t exceeded Vietnam's average (1978-2015) (yes = 1); Cyclone Count_t is the strike count in year t; Cyclone Count_t >avg. is an indicator for whether the cyclone count exceeded Vietnam's average (1978-2015). 'Fraction destroyed' is computed from PWT 8.0 capital stock data and EMDAT storm damage estimates for 1990-2015. OLS regressions omit a constant. Robust S.E.s in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).

The results confirm a positive and significant effect of cyclone strikes and intensity on damages as a fraction of the capital stock. As a final step, we add these damages to the benchmark capital depreciation rate estimate for Vietnam provided in the Penn World Tables, which is $\delta_0 = 4.4\%$ (in 2014) so as to derive our state-contingent depreciation rate estimates as laid out in Table 7.[10]

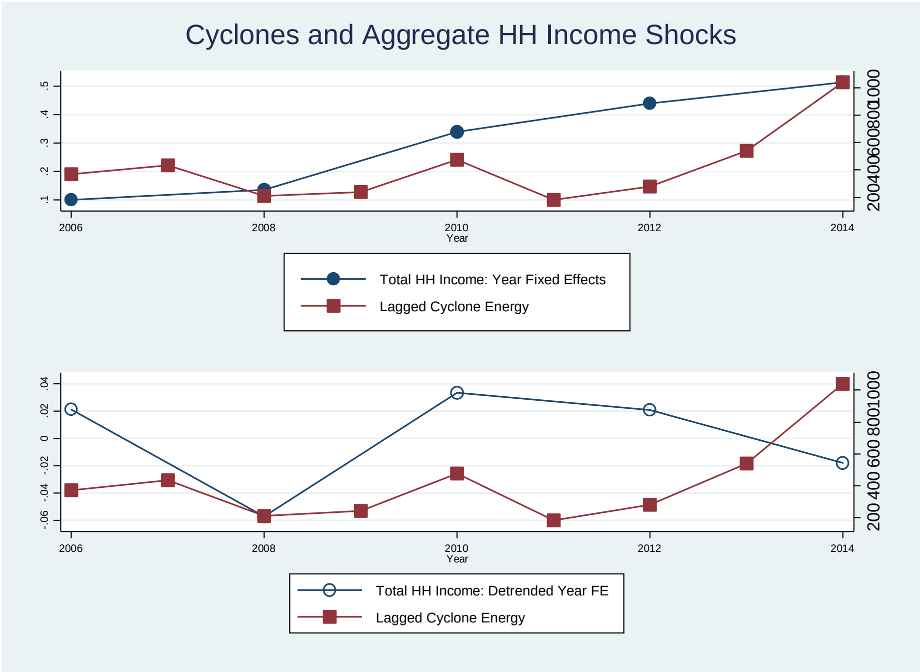
Table 7: Conditional Depreciation Rates

S_t Measure	$\delta(S_t)$
CyCount$_t$ >avg.	
$\delta(S_t = 1)$	0.0445
$\delta(S_t = 0)$	0.0440
Energy$_t$ >avg.	
$\delta(S_t = 1)$	0.0448
$\delta(S_t = 0)$	0.0440

4.5 Total Factor Productivity

In order to gage the effects of cyclone activity on total factor productivity, $A(S_t)$, we consider two sources of evidence. Our main approach conducts a standard growth accounting exercise to estimate an aggregate total factor productivity (TFP) series for Vietnam, and then studies its relationship with cyclone activity. However, for completeness we first also consider the time-fixed effects $\widehat{m_t}$ from income regressions (13) as measure of aggregate shocks to each income-generation activity. In particular, we de-trend the coefficients (so as to remove the secular and non-stationary growth component) and use the residual variation to measure aggregate fluctuations. Figure 5 illustrates both the raw and linearly detrended $\widehat{m_t}$ series for households' total income (from all sources). Figure 6 provides a breakdown by income sources.

[10] It should be noted that we do not calibrate to match $E[\delta(S_t)] = 4.4\%$, but rather take the PWT figure as a baseline to which the estimated cyclone impacts are added. This is because PWT uses U.S.-based depreciation rates for specific capital goods (e.g., software vs. structures) and the composition of Vietnam's capital stock to estimate its depreciation rate (Inklaar and Timmer, 2013). That is, the PWT estimates of Vietnam's depreciation rate do not already reflect cyclone-specific impacts. Consequently, we add them to the baseline rate.



Cyclones and Aggregate HH Income Shocks
.1
.2
.3
.4
.5
2006
2008
2010
2012
2014
Year
200400600800
1000
Total HH Income: Year Fixed Effects
Lagged Cyclone Energy
-.06
-.04
-.02
0
.02
.04
200 400 600 800 1000
Total HH Income: Detrended Year FE
Lagged Cyclone Energy

Figure 5

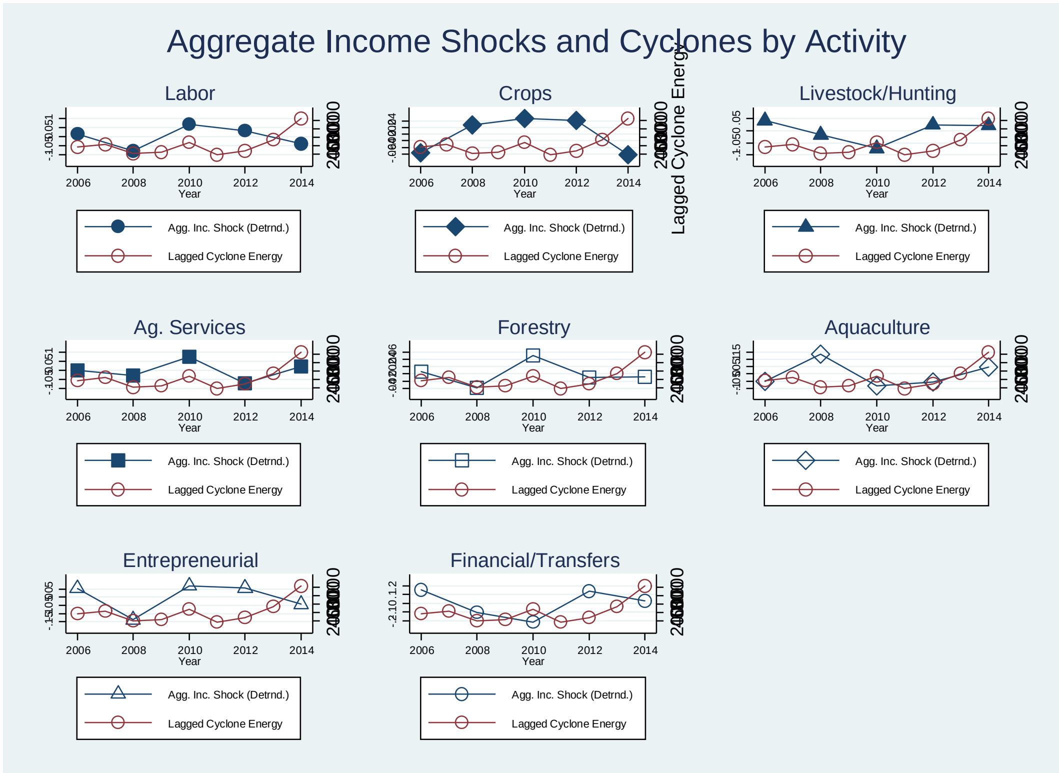


Figure 6

Unfortunately, the survey provides only very limited temporal variation to identify any association between $\widehat{m_t}$ and cyclone activity. Six survey waves leave us with five time fixed effects, one of which is dominated by the effects of the Great Recession 2008. Due to both this data paucity and the desire to calibrate our model to formal measures of TFP, we thus focus on aggregated data for the calibration.

We construct a TFP data series for Vietnam based on a standard growth accounting exercise.[11] This approach first specifies a standard Cobb-Douglas production function for GDP Y_t as function of aggregate capital K_t and effective labor (human capital H_t times labor force L_t):

$$Y_t = A_t K_t^{\alpha} (H_t L_t)^{1-\alpha}$$

Taking logs on both sides and rearranging yields:

$$\ln(A_t) = \ln(Y_t) - \alpha \ln(K_t) - (1-\alpha) \left[\ln(H_t) + \ln(L_t)\right] \tag{22}$$

[11] While the Penn World Tables provide ready-made real TFP series for a number countries, this is not the case for Vietnam, necessitating this decomposition.

The Penn World Tables provide data on real ($2011) values of Vietnam's GDP $\ln(Y_t)$, capital stock $\ln(K_t)$, a human capital index $\ln(H_t)$, and the number of persons engaged in the labor force ($\ln(L_t)$). Given an estimate of the capital share α, one can thus back out TFP using (22). We first obtain available labor share estimates (also from the Penn World Tables) in the region, namely for the Philippines, Thailand, and Laos. The average labor share is around 0.4, considerably below the standard U.S. value of 0.67. Presumably, this is due to the informal sector's contribution to labor compensation, biasing the National Accounts-based labor share estimate downward. We thus consider labor share estimates of both 0.4 and 0.6. Figure 7 presents the raw $\ln(A_t)$ series for both measures, plotted against cyclone energy in each year. Neither series appears correlated with cyclone activity. In order to test more formally for cyclone strike impacts on TFP *shocks*, we proceed to detrend the series both linearly and through HP-filtering.[12]

Figure 8 displays the resulting TFP shock series against cyclone energy for the preferred labor share value of 0.6. Once again, neither series visually appears to respond negatively to cyclone activity.

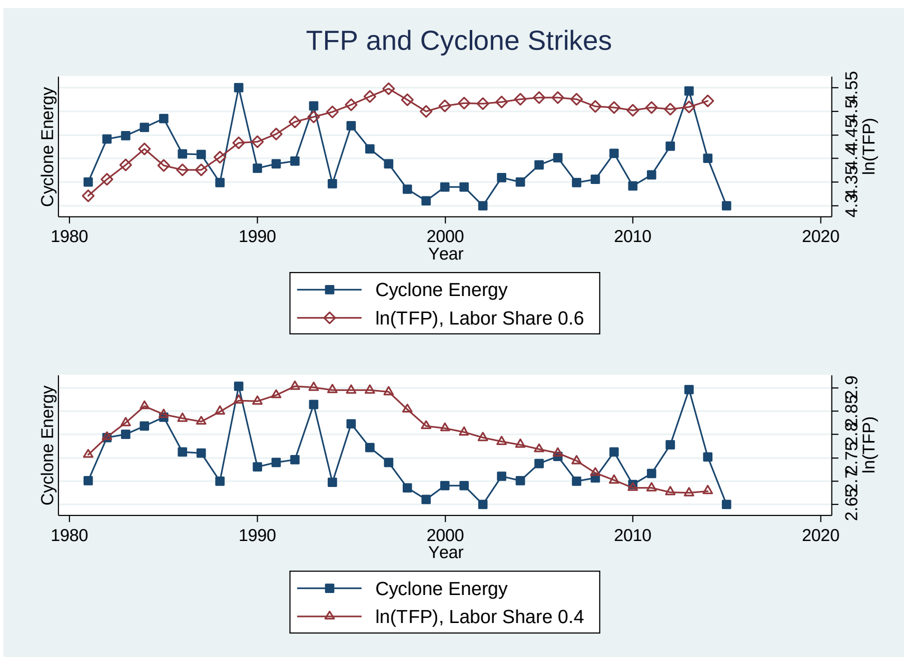


Figure 7

[12] We use a smoothing parameter of $\lambda = 6.25$, in line with the standard recommendation for annual data (Ravn and Uhlig, 2002).

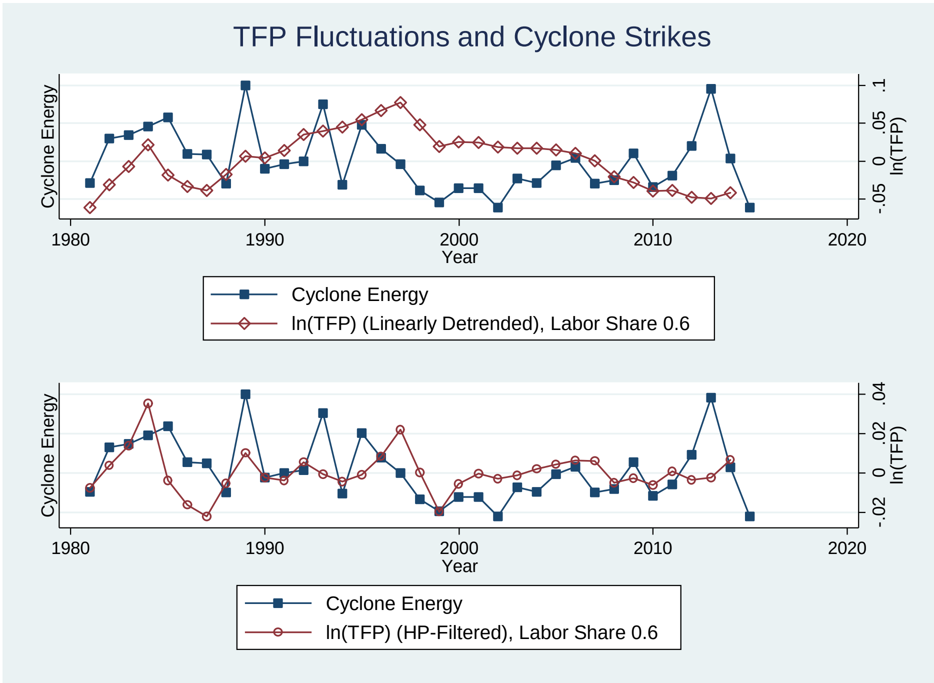


Figure 8

Table 8 provides results of regressions of the TFP measures on both contemporaneous and lagged cyclone activity. We fail to detect a significant negative impact of cyclone strikes on TFP across all specifications.

Table 8: Aggregate Total Factor Productivity and Cyclone Strikes

Dependent Variable: Aggregate $\widehat{\ln A_t}$ in Levels or Deviations from Trend								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CyCount_t	-0.007	-0.010	0.001					
	(0.014)	(0.008)	(0.002)					
CyCount_{t-1}	0.000	-0.004	0.002					
	(0.014)	(0.008)	(0.002)					
CyCount_t >avg.				-0.013				
				(0.013)				
Energy_t					-0.000	-0.000	0.000*	
					(0.000)	(0.000)	(0.000)	
Energy_{t-1}					-0.000	-0.000	0.000	
					(0.000)	(0.000)	(0.000)	
Energy_t >avg.								-0.014
								(0.013)
Year		0.005***		0.005***		0.005***		0.005***
		(0.001)		(0.001)		(0.001)		(0.001)
Constant	4.480***	-5.689***	-0.002	-5.416***	4.515***	-5.266***	-0.006	-5.279***
	(0.017)	(1.271)	(0.003)	(1.275)	(0.024)	(1.355)	(0.004)	(1.287)
$\widehat{\ln A_t}$ Detrending	No	Linear	HP-Filt.	Linear	No	Linear	HP-Filt.	Linear
Observations	34	34	34	34	34	34	34	34
Adjusted R^2	-0.055	0.652	-0.027	0.654	0.042	0.638	0.047	0.657

Table presents results for OLS regression of natural log of TFP (in levels or detrended) on indicated cyclone activity variables. Standard errors in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).

The regression results thus appear consistent with the idea that cyclone strikes do not exert a large or significant impact on total factor productivity. Of course, one may wonder if this result is driven by the focus on Vietnam which - while subject to frequent storms - does not usually experience cyclones at the upper end of the intensity distribution. However, conducting this type of analysis for the Philippines - one of most cyclone-vulnerable countries in the world - we similarly fail to find a significant negative effect of cyclones on TFP (see Appendix). Nonetheless, for the benchmark calibration, we take the point estimates from Table 2 at face value. In particular, we assume that TFP decreases by -1.3% if CyCount_t >avg., and by -1.4% if Energy_t >avg. The level of TFP is calibrated to match Vietnam's observed base year (2014) real growth rate of 5.8%, as described below.

4.6 Cyclone Risk Distributions

The final critical piece of the calibration is the probability distribution of cyclone states in the baseline and climate change scenarios. To this end, we combine historical cyclone track information from IBTrACs with synthetic cyclone track simulations from Kerry Emanuel and co-authors (Emanuel, 2008; Emanuel, Sundararajan, and Williams, 2008). Simulated cyclone track data were generated by Emanuel using the following process: First, given inputs from general circulation models to set climate parameters, potential cyclones are randomly seeded across relevant simulated ocean basins. Given local conditions, seeds either develop into a cyclone or (for a majority of cases) die out. Second, conditional on seed genesis, the cyclone *track* is modeled using a so-called 'beta-and-advection' model based on broad-scale wind fields, and tracked until dissipation. Lastly, cyclone intensity is estimated using a deterministic model coupling atmospheric and oceanic conditions (Emanuel, Sundararajan, and Williams, 2008). The results are synthetic storm tracks that contain parallel information to the historical record in IBTRACs, including simulated storm latitude, longitude, wind speed, and minimum sea level pressure at points along the track life. The authors provide simulated storm tracks for both the 1981-2000 period, and using projected climatic conditions in 2081-210 assuming the IPCC's AR1b emissions scenario and its projected impacts from four climate models: CNRM, ECHAM, GFDL, and MIROC.

Emanuel's cyclone track data can be used directly to compute conditional means of the distribution of future cyclone characteristics (i.e., conditional on a cyclone existing and making landfall). However, for the purposes of the model, we need to know the probability distribution of cyclone states in Vietnam *per year*, not per storm. We thus conduct a Monte Carlo simulation proceeding in the following steps. First, we use the Emanuel cyclone frequency data to estimate the projected future mean number of storms making landfall in Vietnam each year. Specifically, we (i) take the historical mean number of cyclones making landfall in the Western Pacific basin each year (26.6) as a benchmark; (ii) note that the future fraction of simulated storms in the Western Pacific making landfall in Vietnam in particular remains almost identical to today's climate,[13] (iii) apply the projected percentage increase in the frequency of Western Pacific landfall-making cyclones from each climate model to infer the projected mean number of storms[14] making landfall in Vietnam, as shown in Table 9.

[13] Specifically, the fraction of simulated cyclone tracks making landfall in Vietnam in the current climate are: 7.8% (ECHAM), 11.2% (CNRM), 10.7% (GFDLCM), and 17.9% (MIROC). In contrast, among future simulated tracks, the corresponding percentages are: 7.3% (ECHAM), 11.2% (CNRM), 7.6% (GFDLCM), and 14.4% (MIROC).

[14] Note that these simulations include storms with wind speeds below the Saffir-Simpson Category 1 cutoff (33 m/s and above). Consequently, the storm count Count_t variable is different from the CyCount_t variable as defined in Table 4.2.

Table 9: Vietnam Landfall Frequencies					
Variable	Current	2080-2100			
		CRNM	ECHAM	GFDLCM	MIROC
$\mu(\text{Count}_t^{\text{Vietnam}})$	5.2	5.69	5.64	5.90	5.35

Second, we assume a Poisson distribution of cyclone counts to randomly sample the *number* of storms making landfall per year under the future climate. The Poisson assumption fits the historical distribution reasonably well, with similar mean and variance in cyclone counts (5.2 and 5.9 for Vietnam in the 1978-2015 period). Figure 9 showcases the density of historical cyclone counts in Vietnam against simulated ($n = 1,000$) counts under a Poisson(5.2) distribution:

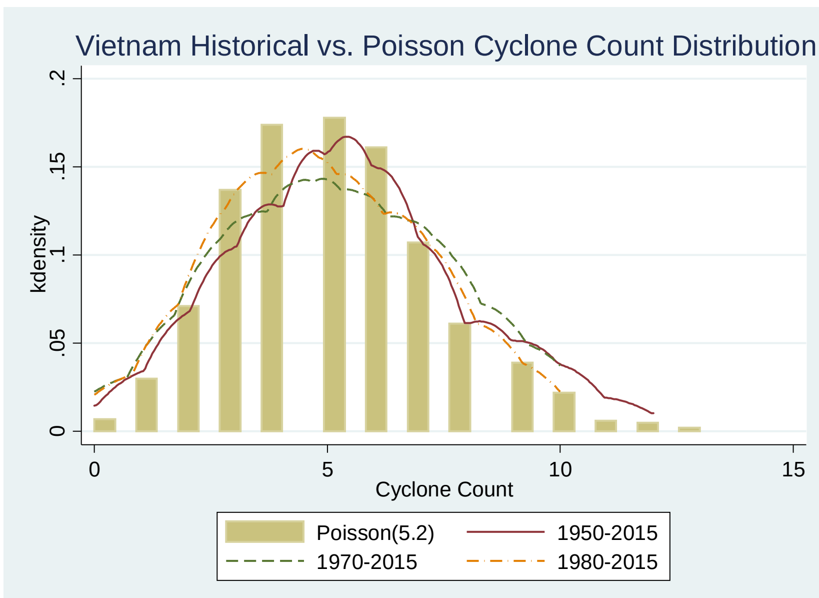


Figure 9

Importantly, the Poisson assumption also implies that the projected change in the mean number of landfalls is sufficient to characterize the future distribution of landfall counts. Consequently, we take $n = 1,000$ draws from the Poisson($\widehat{\mu_{2100}}$) distribution for projected future means from each climate model as per Table 4.6.

Third, for each draw of a *number* of storms making landfall, we then randomly sample the trajectory and characteristics of one of the 3,000 simulated future storm tracks in the Emanuel data (with replacement). This process thus generates random draws over *annual* cyclone realizations in a given year in the future, including years without storms. The probability that dissipated cyclone energy in a given year exceeds its current average value may thus increase both because storms are getting stronger, and because the probability of a larger number of storms is higher in the future. Table 10 summarizes the simulation results for projected changes in the probability distribution and average characteristics of cyclones under each climate model. The intensity of storms is projected to increase significantly, with average annual energy projected to increase by a factor of 3 or 4. The probability of being in a 'high' cyclone state (as currently defined) essentially doubles for both of our benchmark state variables.

Table 10: Monte Carlo: Current vs. Future Cyclone State Probability Distributions

Measure	Current	2080-2100			
		CRNM	ECHAM	GFDLCM	MIROC
$\Pr(\text{Energy}_t > \overline{\text{Energy}_{1978-2015}}$	42.11%	82.50%	86.30%	85.20%	88.30%
$\Pr(\text{CyCount}_t > \overline{\text{CyCount}_{1978-2015}})$	47.37%	84.10%	88.90%	86.90%	91.30%
$\Pr(\text{Count}_t > \overline{\text{Count}_{1978-2015}})$	44.74%	50.5%	49.30%	52.40%	43.90%
$\mu(\text{Energy})$	397,030	1,180,169	1,259,737	1,403,682	1,710,839
$\mu(\text{CyCount})_{1978-2015}$	0.61	1.82	2.09	2.11	2.37
$\mu(\text{Count})$	5.20	5.69	5.64	5.90	5.35
$\mu(\text{Wind Max})$	55.92	78.65	79.50	83.45	89.92

5 Simulations

This section uses the empirical quantifications of cyclone impact and probability changes from Section 4 to calibrate the model outlined in Section 3. The parameters are set in two stages: First, the set of pre-determined parameters are summarized in Table 11.

Table 11: Benchmark Parameters

	Cyclone State Measure S_t :	
	Energy_t>avg.	CyCount_t>avg.
$\delta(S_t = 1)$	0.0448	0.0445
$\delta(S_t = 0)$	0.0440	0.0440
$\sigma^2_\eta(S_t = 1)$	0.113	0.117
$\sigma^2_\eta(S_t = 0)$	0.060	0.070
$\frac{A(S_t=1)}{A(S_t=0)} - 1$	-0.014	-0.013
$\pi_{2000}(S_t = 1)$	0.4211	0.4737
$\pi_{2100}(S_t = 1)$	0.85	0.87

In addition, the benchmark calibration sets preference parameters $\gamma = 1.5$ and $\beta = 0.95$. We also consider logarithmic preferences ($\gamma = 1$) and re-calibrate $\beta = 0.9236$ in this scenario to match the initial savings rate of the benchmark. We further follow Krebs (2003) in approximating $N(0, \sigma_\eta^2(S_t))$ with a discrete random variable equal to $+\sigma_\eta(S)$ or $-\sigma_\eta(S)$ with equal probability.

Second, the computation solves for the base level of total factor productivity ($A(S_t = 0)$) jointly with the optimal capital type ratio $\widetilde{k}$ and consumption rate $\widetilde{c}$ in order to match the moment that initial GDP growth equal base year (2014) observed real growth in Vietnam (5.8%). Finally, we iterate over values of the income share parameter α to match households' observed average income ratios from each group (21) in the VHLSS survey:

$$
\begin{aligned}
E[Y_{t+1}/Y_t] &= 1.058 \\
E[y_{1it}/y_{2it}] &\approx 10.5
\end{aligned}
$$

Tables 12 and 13 present the results for the benchmark calibration (with $\gamma = 1.5$) and for logarithmic preferences ($\gamma = 1$), respectively. The impacts of climate change can be summarized as follows. First, the model predicts adaptation: households increase their investment in income-generating assets K_1 that are not vulnerable to idiosyncratic shocks from cyclones (e.g., human capital for salaried labor), and decrease investment in assets K_2 subject to such shocks (e.g., animals). Second, the model predicts precautionary savings: households increase their savings rates (i.e., decrease $\widetilde{c}$) in response to climate risks when $\gamma > 1$. Third, climate change-induced shifts in the cyclone distribution are predicted to depress asset returns and long-run growth in Vietnam. The benchmark estimates imply a growth rate decline of $0.7 - 0.14$ percentage points - on the same order of magnitude as recent estimates of the long-run growth rate impact of business cycles in the United States (Krebs, 2003; Barlevy, 2004). Finally, the associated welfare effects - measured as percentage of initial period consumption agents would be willing to forgo to avoid climate change - range from 0.85% to 12.75%.

Table 12: Climate Change Impacts ($\gamma = 1.5$, $\beta = 0.95$)

	Incomplete Markets				Complete Markets	
	Energy>avg.		CyCount>avg.		CyCount>avg.	
	2015	2100	2015	2100	2015	2100
$\widetilde{k} = \frac{K_1}{K_2}$	5.9884	6.0117	5.2634	5.2834	5.2112	5.2110
$\widetilde{c}$	0.0764	0.0760	0.0763	0.0760	0.0764	0.0761
$E[r_{it}]$	14.55%	14.40%	14.54%	14.43%	14.54%	14.42%
$E[g_{it}]$	5.80%	5.71%	5.80%	5.73%	5.79%	5.72%
$\Delta W(\%\Delta C_0)$	-	-1.09%		-0.88%		-0.84%
$A(S_t = 0)$	0.2883		0.2967		0.2967	
α	0.856		0.839		0.839	
$E[y_{1t}/y_{2t}]$	10.51		10.49		5.2112	

Table 13: Climate Change Impacts ($\gamma = 1, \beta = 0.9236$)

	Incomplete Markets				Complete Markets			
	Energy>avg.		CyCount>avg.		Energy>avg.		CyCount>avg.	
	2015	2100	2015	2100	2015	2100	2015	2100
$\widetilde{k} = \frac{K_1}{K_2}$	5.9497	5.9645	5.2077	5.2210	5.9197	5.9197	5.1728	5.1728
$\widetilde{c}$	0.0764	0.0764	0.0764	0.0764	0.0764	0.0764	0.0764	0.0764
$E[g_{it}]$	5.80%	5.66%	5.80%	5.69%	5.80%	5.67%	5.80%	5.69%
$E[r_{it}]$	14.55%	14.40%	14.55%	14.43%	14.55%	14.55%	14.55%	14.43%
$\Delta W(\%\Delta C_0)$	-	-12.76%	-	-4.89%	-	-12.75%	-	-4.86%
$A(S_t = 0)$	0.2887		0.2973		0.2887		0.2973	
α	0.8555		0.838		0.8555		0.838	
$E[y_{1t}/y_{2t}]$	10.5332		10.5061		5.9206		5.1728	

Table 14 presents results for three robustness checks. The first considers larger capital damages, increasing the depreciation rate with high cyclone activity from 0.044 to 0.054. The assumption that above-average cyclone activity increases capital depreciation by a full percentage point is arguably extreme. For comparison, given the current U.S. capital stock value estimate of \$52.85 trillion US \$2011 (PWT), this assumption would require a high hurricane activity year to induce \$528 billion dollars worth of direct damages. In reality, even Hurricane Katrina - the costliest in U.S. history - induced "only" an estimated \$108 billion of direct damages. The growth impacts in this scenario are large - a decline of 0.3 percentage points - and the associated welfare costs are more than triple the benchmark scenario. Nonetheless, the estimated impacts remain broadly in the range of the benchmark cases. The next column uses an alternative moment to match in the calibration of α, the income share of K_1. While the benchmark scenario matches to the *average* income ratio in the VHLSS data (10.53), column (2) matches the median value for $\frac{y_{1it}}{y_{2it}}$ (1.29). Intuitively, this specification assigns a relatively higher importance to vulnerable income-generating activities. While the projected welfare costs of climate change increase as a result, both the growth effects (-0.05 percentage points) and the welfare costs (-1.43% of initial consumption) are broadly in line with the other scenarios. Finally, column (3) doubles the assumed effect of cyclones on total factor productivity (from -1.3% to a -3% decline). Again, while this scenario results in a substantial growth impact (-0.15 percentage points) and an increase in welfare costs, the figures are in line with the benchmark.

Table 14: Sensitivity ($\gamma = 1.5$, CyCount>avg.)

	(1)		(2)		(3)	
Robustness:	$\delta(1) = 0.054$		Target $E[y_{1t}/y_{2t}]$ =1.29		$[\frac{A(S_t=1)}{A(S_t=0)} - 1] = -3\%$	
	2015	2100	2015	2100	2015	2100
$\widetilde{k} = \frac{K_1}{K_2}$	4.8309	4.8503	0.6780	0.6879	5.1422	5.1627
$\widetilde{c}$	0.0763	0.0750	0.0756	0.0750	0.0763	0.0757
$E[g_{it}]$	14.54%	14.05%	14.45%	14.33%	14.54%	14.30%
$E[r_{it}]$	5.8%	5.5%	5.8%	5.75%	5.8%	5.65%
$\Delta W(\%\Delta C_0)$	-	-3.65%	-	-1.43%	-	-1.82%
$A(S_t = 0)$	0.3097		0.3715		0.3007	
α	0.8270		0.395		0.8358	
$E[y_{1t}/y_{2t}]$	10.5258		1.2959		10.5365	

6 Conclusion

How will climate change-induced shifts in extreme weather risk distributions affect economic activity, outcomes, and welfare? This paper applies the tools from the macroeconomics literature on the cost of business cycles to estimate the welfare costs of changes in tropical cyclone risks in general equilibrium. We develop a quantitative version of Krebs' (2003) stochastic endogenous growth framework with idiosyncratic and aggregate risks applied to the context of Vietnam. An empirical analysis of cyclone impact channels reveals the following. First, cyclone strikes appear to significantly increase the variance of idiosyncratic shocks to households engaged in certain income-generating activities, such as agriculture and animal husbandry. Second, cyclone strikes also induce aggregate risks through capital destruction. While we empirically fail to detect a significant negative effect of cyclone strikes on total factor productivity, the calibration considers this impact channel as well. Finally, based on future synthetic cyclone track simulations from Emanuel (2008), we estimate that the probability of Vietnam being in a "high" cyclone state increases dramatically for all cyclone state variables currently considered. Utilizing these empirical results to calibrate the model, the central result is that changes in future cyclone risk distribution are expected to depress Vietnamese long-run growth by an economically significant $0.07 - 0.14$ percentage points. These impacts are on par with estimates for the growth costs of U.S. business cycles (e.g., Krebs, 2003; Barlevy, 2004). The welfare costs of these changes are estimated at $0.85 - 12.75\%$ of initial consumption.

The model hopes to contribute to the literature by proposing a structural approach to linking weather impact estimates to climate change impact predictions. The model creates a two-way dialogue with the data: On the one hand, the model provides specific weather impact channels that need to be estimated in the data. On the other hand, the model uses these weather impact estimates to project the effects of climate change by formally modeling households' behavior as a function of the distribution of weather risks. That is, the model accounts explicitly for adaptation on two extensive margins: household savings rates and the composition of investment in more- or less-vulnerable assets. At the same time, an important shortcoming of the model is that it does not (yet) account for intensive margin adaptation. That is, the effects of cyclone strikes on, e.g., capital depreciation, are assumed to stay that same over time. To the extent that infrastructure can be built to be more resilient, the estimated impacts thus represent an upper bound.

The next steps are to address some of the most critical limitations of the present analysis. For example, the analysis thus far considered only binary cyclone state variables; a richer representation will provide a more accurate reflection of changes in the tails of the cyclone risk distribution. Finally, we are collecting and processing data from other countries. As many countries around the world are poised to experience significant changes in cyclone risks over the 21st century, understanding their impacts on economic activity and human welfare remains an important and open question.

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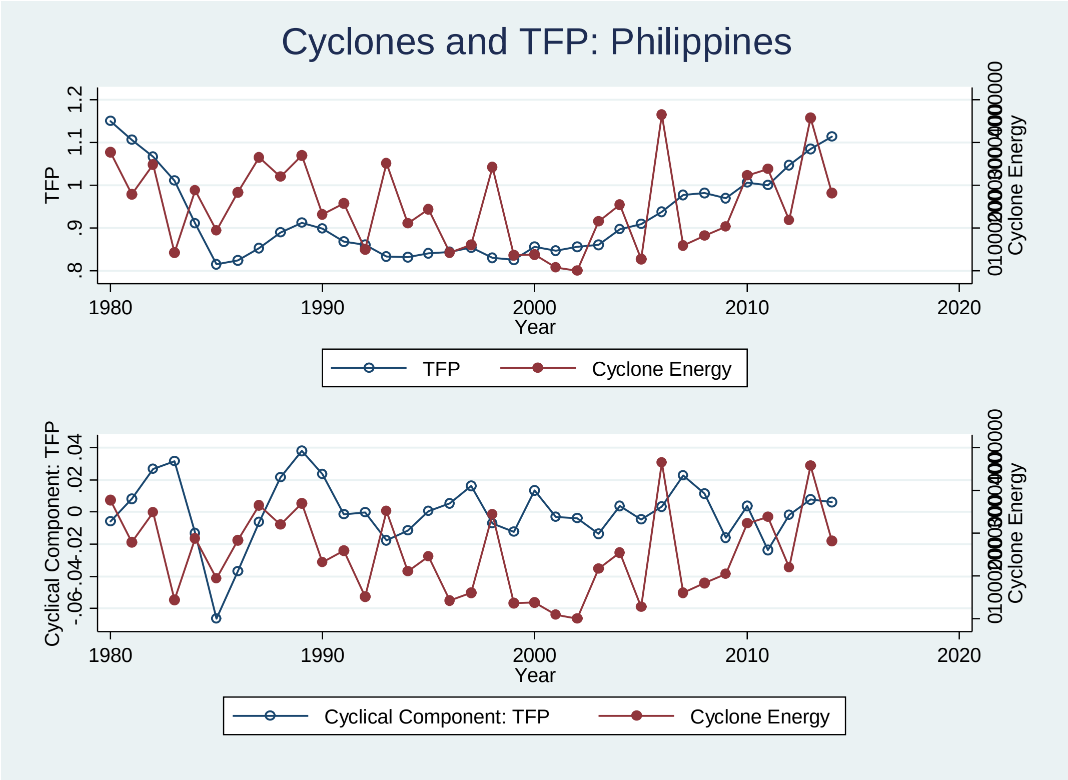
7 Appendix

Table A1: Predictable Household Income

Dependent Variable: Total Earnings from Income Category		
	$Y_{2,it}$	$Y_{1,it}$
HH Share Male	0.195***	-0.042
	(0.058)	(0.053)
HH Avg. Education	0.055***	0.089***
	(0.007)	(0.006)
HH Avg. Age	0.008***	-0.002
	(0.002)	(0.002)
HH Size	0.209***	0.000
	(0.008)	(0.009)
HH Head's Age	0.014	0.092***
	(0.015)	(0.016)
(HH Head's Age)^2	-0.000	-0.001***
	(0.000)	(0.000)
HH Head Education	-0.026***	0.098***
	(0.004)	(0.004)
Constant	7.144***	6.377***
	(0.277)	(0.290)
Year Fixed Effects:	Yes	Yes
Observations	18,169	24,628
Adjusted R-squared	0.140	0.185

Table presents results for OLS regression of $\log(Y_{j,it})$ on the indicated variables. $Y_{2,it}$ is income from crops, livestock, forestry, aquaculture, and ag. services. $Y_{1,it}$ is income from salaried labor, non-ag. entrepreneurial activity, financial assets, transfers, remittances, scholarship, health aid. Standard errors clustered at the household level. (*** p<0.01, ** p<0.05, * p<0.1).



Cyclones and TFP: Philippines
TFP
Cyclone Energy
Year
Cyclical Component: TFP

Figure A1

Table A3: Aggregate TFP and Cyclone Strikes: Philippines

Dependent Variable: Aggregate A_t in Levels or Deviations from Trend			
	(1)	(2)	(3)
Energy_t	0.000*	0.000**	0.000
	(0.000)	(0.000)	(0.000)
Energy_{t-1}		0.000***	0.000
		(0.000)	(0.000)
Year	0.003*	0.003**	
	(0.001)	(0.001)	
Constant	-4.744	-5.629**	-0.009
	(2.910)	(2.572)	(0.008)
$\widehat{\ln A_t}$ Detrending	Linear	Linear	HP-Filter
Observations	34	34	34
Adjusted R^2	0.144	0.339	0.006

Table presents results for OLS regression of PWT estimates of Philippine TFP (in levels or detrended) on indicated cyclone activity variables. Standard errors in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).