Economics of Climate Change

Referee Report on: *Flooding and Firms in Indonesia* by Azhar Hussain

Ezékiel TANO, Master 2 PPD (Paris School of Economics)

1 Recommandations

I recommend major revisions and resubmission. The paper is strong in both empirical and theoretical aspects, but several critical areas especially related to identification, behavioral assumptions, and policy scope require deeper exploration.

2 Overview of the paper

This paper examines how flooding affects the behavior and performance of firms in Indonesia, a lower-middle-income country that is highly vulnerable to climate-related disasters, especially floods. The study is motivated by the fact that extreme weather events are becoming more frequent and intense in developing countries, yet we still know relatively little about how firms in these contexts adapt or respond to such risks.

To do this, the author uses two main methods. The first part is an empirical analysis that focuses on the short-term, direct effects of flooding. This is done using a difference-in-differences (DiD) approach, which compares changes in outcomes across regions and years with different levels of flood exposure. A key innovation here is the construction of a flood index that captures both how large the flooded area is and how long the flooding lasts. This allows the author to capture not just whether a flood occurred, but how intense it was. Using this approach, the paper shows that severe floods significantly reduce aggregate economic performance: output, capital investment, and the number of new firms entering the market all decline. Interestingly, however, the number of employees particularly temporary workers, tends to increase in the short run. This suggests that firms try to cope with the disruption by substituting labor for damaged or risky capital. This response appears to be a short-term adaptation strategy, allowing firms to maintain operations without committing to long-term investments that might be destroyed in future floods.

The second part of the study is a quantitative general equilibrium model that aims to understand how firms make decisions under uncertainty about future flood risks. Unlike the first part, which looks at what happens after a flood, this model focuses on how firms anticipate risk and adjust their behavior before a flood occurs. The model includes heterogeneous firms that differ in productivity and face the decision to enter the market, how much capital to invest, and how much labor to hire. Crucially, firms make their capital decisions before knowing whether a flood will happen, but they adjust labor afterward. This reflects the real world constraint that capital is costly and relatively irreversible in the short term, while labor can adjust more flexibly to realized shocks. Flood risk is introduced into the model through a region and time specific shock that reduces the effective use of capital during a flood. This is calibrated using production capacity utilization (PCU) data, showing how much of a firm's potential production capacity is actually used which serves as a proxy for how much disruption the firm experiences. The model helps explain why firms located in flood-prone areas may under-invest in capital even if no flood occurs: they expect that some of that capital may be wasted.

To test the broader implications of this behavior, the author runs a policy simulation in which flood-prone regions are protected with flood defenses, such as levees or drainage systems. The results show that such policies do increase aggregate economic output, because they reduce uncertainty and make firms more willing to invest. However, the model also reveals a downside: the improved conditions attract less productive firms, which now find it profitable to enter the market. These new entrants push up wages by increasing demand for labor, which partially cancels out the benefits of higher investment. This shows that even well-intentioned climate adaptation policies can have unintended general equilibrium effects. The data used in the study comes from two main sources. The flood data is provided by the Dartmouth Flood Observatory (DFO), which uses satellite imagery and other sources to track large flood events over time. The firm-level data is drawn from the Indonesian Annual Census of Medium and Large Manufacturing Establishments (Statistik Industri), a rich dataset that includes detailed information on firm-level performance, investment, employment, and geographic location.

In sum, the paper finds that floods harm firms both directly and indirectly. More importantly, the fear of future floods perceived flood risk can change firm behavior in significant ways, leading to lower investment and distorted resource allocation. While flood defenses can help, they also generate secondary effects that need to be taken into account. These findings have important implications for designing effective climate adaptation policies in developing countries

3 Comments and Suggestions

3.1 Major Comments

3.1.1 Identification Strategy, Endogeneity, and Robustness:

A central strength of the paper lies in its empirical framework, particularly the combination of a difference-in-differences approach with a continuous flood index. This index captures both spatial spread and duration of floods, allowing for more nuanced analysis. However, The causal interpretation hinges on assumptions that merit deeper discussion and empirical validation.

- *(i) Endogeneity of Flood Exposure:* Firms do not randomly choose their location. More financially capable, better connected, or more experienced firms may intentionally locate in flood-prone areas because of lower land prices, proximity to rivers and ports, or access to large markets. These firms might also be more resilient to disasters, have better insurance coverage, or access to government support. These unobserved factors could be correlated with both location and firm outcomes, introducing omitted variable bias. This endogeneity concern parallels those raised in infrastructure studies such as *Donaldson (2018)*, where treatment exposure was not independent of initial economic conditions.

- *(ii) Measurement Bias from Economic Activity:* While the flood index is built from satellite and remote-sensing data, it may still be indirectly influenced by local economic development. Regions with higher economic activity often attract more governmental and institutional attention, including better climate surveillance and flood detection infrastructure. As a result, floods in economically important areas may be detected more frequently or with higher precision. This could lead to a non-random measurement of exposure. *Bakkensen and Barrage (2020)* showed that disaster visibility is often uneven, and this can bias economic impact estimates. The author should acknowledge this and, if possible, quantify its likely effects.

- *(iii) Suggested Empirical Enhancements:* To address the concerns above, the paper could incorporate several complementary strategies. Instrumental variable approaches using plausibly exogenous climatic variations such as upstream rainfall shocks, historical river overflow patterns, or lagged hydrological cycles could strengthen identification. Placebo tests on unaffected sectors (e.g., professional services, remote firms) or on pre-flood periods can help rule out confounding time trends. Additionally, matching methods like propensity score matching would improve comparability between exposed and unexposed firms by balancing observed characteristics, as applied in disaster economics literature (*Deryugina et al., 2018*). These instruments must, however, be tested for exclusion restrictions and relevance, to avoid introducing further bias. These potential biases must be accounted for to ensure that estimated flood impacts are not confounded by firm-level resilience or selection.

3.1.2 Measurement of Flood Risk and Anticipatory Behavior:

The paper's theoretical contribution lies in its focus on how firms adjust their investment decisions not just in response to realized shocks but also based on expected risk. While the conceptual innovation is clear, the empirical identification of perceived risk effects requires stronger support. PCU is an ex-post outcome influenced by both flood perception and other operational factors such as supply chain disruptions or seasonal demand variation. Its interpretation as a pure anticipatory proxy must be treated cautiously.

- *(i) Use of Proxies for Expectations:* The study uses historical flood exposure and firm-level production capacity utilization (PCU) as proxies for flood risk perception. The logic is that past exposure lowers capital usage in anticipation of future shocks. However, this rests on a strong assumption: that all firms form expectations similarly and that they respond to the same flood history in the same way. In reality, firms may differ substantially in how they form beliefs based on exposure, experience, and capacity to adapt, depending on access to information, past losses, financial literacy, or managerial risk preferences. *Cai (2022)* demonstrates that recent and visible events tend to have a stronger influence on perceived risk than long-term trends.
- *(ii) Incomplete Capture of Risk Perceptions:* Firm expectations are shaped by more than just direct flood history. Media coverage, public warnings, disaster drills, peer behavior, and even financial market indicators (such as rising insurance premiums or declining land values) all contribute to how firms assess future risk. For example, a firm might act conservatively if it sees nearby competitors affected, even if it was not directly impacted. These pathways are not captured by PCU or flood exposure frequency alone. As a result, there is a risk of measurement error that could attenuate or misrepresent the true behavioral adjustment.
- *(iii) Suggested Empirical Extensions:* To strengthen the connection between theory and data, the author could use or reference survey data from business owners on risk perception where available. Alternatively, the paper could assess whether changes in PCU are correlated with other observable behaviors such as purchase of insurance, participation in climate risk training, or investment in disaster-proof infrastructure. *Bolton and Kacperczyk (2021)* highlight how indirect behavioral signals can be leveraged to assess risk perceptions in financial markets. A similar logic could apply here, reinforcing PCU as a credible proxy for anticipatory decision-making.

3.1.3 External Validity and Generalization:

Indonesia is a salient case given its frequent exposure to climate shocks, but the external validity of results remains context-dependent. Even a brief comparative section would help situate the Indonesian case within the broader Global South.

- *(i) Transferability to Other LMICs:* Although many low- and middle-income countries share Indonesia's exposure to floods, they often differ significantly in institutional quality, financial development, public infrastructure, and labor informality. These factors shape firms' ability to anticipate and respond to climate risks. For example, in countries with weaker institutions or fragile credit systems, firms may not be able to act even if they perceive risk. *Hallegatte et al. (2016)* emphasize that institutional capacity is key to successful adaptation, and the author should consider how these differences might affect external validity.

- *(ii) Comparative Relevance:* A brief comparative discussion with other countries like Bangladesh, Vietnam, or Nigeria would enrich the paper's reach. These countries face similar flood exposure but differ in adaptive governance, insurance penetration, and industrial base. Such comparison would help highlight where the findings may generalize and where context specific limitations arise.
- *(iii) Policy Feasibility and Alternatives:* The paper's main policy focus is on physical flood defenses, which are effective but often capital intensive and politically sensitive. In resource constrained settings, these may not be viable. It would be helpful to contrast them with more flexible or incremental adaptation options such as climate insurance programs, government backed emergency funds, or land use regulations. *Clarke and Dercon (2016)* provide a framework to evaluate disaster preparedness policies based on cost-effectiveness and scalability, which could be integrated into the policy analysis.

3.1.4 Theoretical Model Assumptions, Calibration, and Interpretation:

The structural model offers a valuable lens to study how anticipated flood risks influence firm entry and input decisions. Still, its assumptions and calibration deserve more thorough justification.

- *(i) Model internal consistency:* The model assumes firms use historical flood frequencies to estimate risk, suggesting a form of rational expectations based on past averages. However, behavioral studies show that agents often rely on heuristics, recent experiences, or social cues. *Gigerenzer and Gaissmaier (2011)* explain how firms and individuals simplify decision making under uncertainty through rules of thumb, which can lead to systematic under or overestimation. The model could be enriched by acknowledging or incorporating bounded rationality or adaptive learning. Moreover, using PCU to translate flood exposure into effective capital loss is innovative. However, the method should be described more precisely. For example, does the calibration account for sector-specific differences in capital intensity or sensitivity to flooding? Are regional differences in infrastructure quality or flood response capacity considered? Adding clarity here would improve transparency and confidence in the model.
- *(ii) Entry Behavior and Frictions:* The assumption that firms enter with perfect foresight contrasts with their myopic behavior in other parts of the model. This internal inconsistency should be resolved. Additionally, the model does not include frictions common in LMICs such as credit constraints, regulatory burdens, or limited market information that often prevent firm entry or expansion. As *Banerjee and Duflo (2014)* emphasize, these frictions can critically shape firm dynamics and must be factored into realistic models.
- *(iv) Policy Modeling:* The paper should include robustness checks by varying key parameters such as flood frequency, firm productivity distribution, and labor flexibility. Sensitivity analysis would demonstrate the stability of the results and allow policymakers to judge how outcomes change under different economic or environmental conditions. *Moll (2014)* illustrates how capital misallocation models benefit from such checks to reveal equilibrium fragility. While the flood defense simulation shows an aggregate output gain, the welfare consequences are less developed. For example, do new market entrants drive down profits for existing firms? Do higher wages benefit workers enough to offset the entry of less productive firms? Including welfare metrics like consumption-

equivalent variation, income distribution effects, or productivity decomposition across firm types would allow for a more nuanced policy evaluation. The model could also be adapted to simulate the effects of other adaptation tools such as tax incentives for capital in safer areas, or subsidies for insurance premiums to compare efficiency and equity outcomes. Include a decomposition of welfare changes by firm type and worker group, and compare to alternative policy tools (e.g., insurance subsidies, tax relief for capital relocation).

3.2 Minor Comments and Suggestions

- *Sample Scope and Flood Index Design:*
  The exclusion of the Eastern provinces (Papua, Papua Barat, Maluku, and Maluku Utara) is justified on the basis of low population density and sectoral composition (forestry and fishing). However, a brief comparison with the included regions would help assess whether their exclusion introduces sample bias. Additionally, the construction of the flood index using the product of spatial and temporal extent scaled between 0 and 1 is intuitive, but the rationale for this multiplicative form should be clarified and justified with respect to the underlying economic logic. Testing alternative formulations (e.g., additive or log-based) would strengthen the robustness of the results.

- *Heterogeneity Across Sectors and Firms:*
  Figures V and VI highlight differences in sectoral responses to floods, yet they are visually dense and difficult to interpret. Providing a complementary table would enhance clarity. Moreover, the analysis could be deepened by exploring heterogeneity beyond sectors such as firm size, ownership structure, or financial resilience as these factors likely influence how firms adapt to flood risks.

- *Causal Identification and Robustness Checks:*
  While the difference-in-differences strategy is generally sound, further clarification of the identification assumptions is needed. In particular, the paper should address whether flood exposure can be considered exogenous. Including placebo tests or employing matching techniques (e.g., using rainfall variation or upstream flooding) would add credibility to the causal interpretation.

3.3 References:

- Donaldson, D. (2018). "Railroads of the Raj: Estimating the impact of transportation infrastructure." *American Economic Review*, 108(4-5), 899–934. https://doi.org/10.1257/aer.20101199
- Bakkensen, L., & Barrage, L. (2020). "Flood risk belief heterogeneity and coastal home price dynamics: Going under water?" *Journal of Urban Economics*, 117, 103234. https://doi.org/10.1016/j.jue.2020.103234
- Deryugina, T., Kawano, L., & Levitt, S. (2018). "The economic impact of Hurricane Katrina on its victims: Evidence from individual tax returns." *American Economic Journal: Applied Economics*, 10(2), 202–233. https://doi.org/10.1257/app.20160206
- Cai, J. (2022). "Disaster risk and insurance demand: Evidence from a typhoon in China." *Journal of Public Economics*, 204, 104646. https://doi.org/10.1016/j.jpubeco.2021.104646
- Bolton, P., & Kacperczyk, M. (2021). "Do investors care about carbon risk?" *Review of Financial Studies*, 34(3), 817–852. https://doi.org/10.1093/rfs/hhaa007
- Clarke, D. J., & Dercon, S. (2016). *Dull Disasters? How Planning Ahead Will Make a Difference*. Oxford University Press. https://global.oup.com/academic/product/dull-disasters-9780198785576
- Gigerenzer, G., & Gaissmaier, W. (2011). "Heuristic decision making." *Annual Review of Psychology*, 62, 451–482. https://doi.org/10.1146/annurev-psych-120709-145346
- Banerjee, A., & Duflo, E. (2014). *Poor Economics: A Radical Rethinking of the Way to Fight Global Poverty*. PublicAffairs. https://www.pooreconomics.com/
- Moll, B. (2014). "Productivity losses from financial frictions: Can self-financing undo capital misallocation?" *American Economic Review*, 104(10), 3186–3221. https://doi.org/10.1257/aer.104.10.3186
- Balboni, C., et al. (2023). "How Do Firms Adapt to Climate Risk?" *Working Paper*. https://economics.mit.edu/sites/default/files/2023-04/Balboni_FirmAdaptation.pdf
- Cruz, M., & Rossi-Hansberg, E. (2021). "The Economic Geography of Global Warming." *Review of Economic Studies*, 89(1), 46–83. https://doi.org/10.1093/restud/rdab052