Macroeconomic consequences in the aftermath of tropical cyclones : empirical approaches

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Ph.D. DISSERTATION

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Conséquences macroéconomiques associées aux passages des cyclones tropicaux : approches empiriques

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A ma famille, celle sans qui je ne serais,
qui m'inspire et suscite en moi un amour incompressible.
A Lucile, celle qui me permet de réaliser aujourd'hui,
des rêves me paraissant autrefois inaccessibles...

« Homme libre, toujours tu chériras la mer ! »
Charles Baudelaire

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Abstract

Tropical cyclones are arguably one of the most threatening natural disasters for manmade environments. Over the past 50 years, the World Meteorological Organisation estimates the amount of economic losses due to these extreme weather events to 1 400 billion U.S. dollars. Throughout History, the prevention of damages and management of subsequent reconstruction has always represented a perennial challenge to populations living in cyclone-prone areas. This thesis addresses the issue of tropical cyclones' macroeconomic impacts, *i.e.* on main economic aggregates. To begin with, we present a comprehensive literature review that emphasises a wide range of results, but also a variety of cyclone intensity measurements. Then, this thesis investigates the impact of tropical cyclones on economic growth at different scales. Firstly, we distinguish small island developing states and evaluate the impacts on this subgroup of countries. The obtained results are noteworthy as they demonstrate a long-term economic vulnerability as well as hurdles to stimulate their economies in the aftermath of tropical cyclones. As for other countries in the world, in no case are the results significant when these countries are considered as a whole group. However, the latter finding does not mean that other countries cannot be adversely affected by these phenomena. To show this, we provide a case study of the U.S. case. Despite the absence of effect at national scale, a specific analysis of the Floridian case reveals significant growth penalties in the short-run. Hence, the study of the economic impacts of tropical cyclones on a given country should, above all, consider that only small parts of their respective territories may be highly vulnerable to these catastrophes in most cases. Finally, we conclude by evaluating the impact of tropical cyclones on income inequalities in the U.S. This last article unveils beneficial redistributive effects and sheds light on the importance of social benefits in bridging inequalities.

Keywords: Environment; Macroeconomics; Impact evaluation; Tropical cyclones; Natural disasters

Résumé

Les cyclones tropicaux font sans nul doute partie des catastrophes naturelles les plus menaçantes pour les environnements humains sur la surface terrestre. L'Organisation Météorologique Mondiale recense des pertes économiques s'élevant à plus de 1 400 milliards de dollars américains du fait de ces phénomènes météorologiques extrêmes au cours des 50 dernières années. De tout temps, la maîtrise de ces dommages ainsi que la gestion des reconstructions subséquentes ont représenté des enjeux majeurs pour les populations vivant dans les territoires en proie à ces phénomènes. Cette thèse s'intéresse plus particulièrement aux conséquences macroéconomiques induites par les cyclones tropicaux, c'est-à-dire leur impact sur les grands agrégats économiques. Tout d'abord, nous débutons par une revue de littérature exhaustive sur le sujet mettant en exergue, entre autres, des résultats parfois contradictoires mais également une importante diversité des indicateurs de mesure d'intensité cyclonique. Ensuite, cette thèse étudie l'impact des cyclones tropicaux sur la croissance économique, et ce, à différentes échelles. Dans un premier temps, nous nous focalisons sur les petits états insulaires en développement, qui sont au cœur de nombreux débats économiques contemporains. Les résultats sont édifiants et soulignent une fragilité de ces territoires sur le long-terme couplée à des difficultés rencontrées pour se relancer au lendemain des épisodes cycloniques. Quant aux autres pays du monde, aucun effet n'est décelé lorsqu'ils sont étudiés en tant que groupement de pays à part entière. Toutefois, ce dernier résultat ne signifie pas que la croissance économique du reste des pays du monde demeure insensible aux cyclones tropicaux. Pour démontrer cela, dans un troisième chapitre, nous étudions finement le cas des Etats-Unis. Malgré une absence d'effet lors d'estimations à l'échelle nationale, l'analyse distincte du cas floridien révèle des pertes significatives de croissance économique. Ainsi, l'étude des incidences économiques des cyclones tropicaux à une échelle nationale doit avant tout être mise en perspective avec le fait que ces phénomènes sont souvent très localisés. Enfin, nous concluons par une évaluation d'impact sur les inégalités de revenus aux Etats-Unis. Ce dernier article fait état d'un effet redistributif bénéfique lors du passage de cyclones tropicaux, et met en avant l'importance des transferts sociaux dans la correction des inégalités de revenus.

Mots-clés : Environnement; Macroéconomie; Evaluation d'impact; Cyclones tropicaux; Catastrophes naturelles

General introduction

Written in French

Les cyclones tropicaux sont des phénomènes météorologiques extrêmes se formant dans les zones tropicales des océans mondiaux à l'issue d'un processus nommé cyclogenèse. Un système cyclonique est constitué d'une zone de dépression, c'est-à-dire de faible pression atmosphérique, autour de laquelle des vents tourbillonnants et des nuages orageux sont générés. Lorsque l'on se situe dans l'hémisphère sud, la rotation de ces vents s'effectue dans le sens des aiguilles d'une montre, et inversement dans l'hémisphère nord. En tout état de cause, le terme cyclone provient du grec *kyklos*, signifiant littéralement « cercle ».

La zone centrale de basse pression du système cyclonique est appelée « œil », au sein de laquelle l'intensité des vents est faible et les précipitations inexistantes. Le diamètre de l'œil d'un cyclone peut atteindre jusqu'à 15 km. Ce diamètre est délimité par ce qui est qualifié de « mur de l'œil », et qui correspond à la zone où les nuages s'enroulent en spirale. Au-delà de ce mur se manifestent les conséquences météorologiques directes associées à la cyclogenèse, à savoir des pluies diluviennes, ou des vents soutenus une minute pouvant atteindre 345 km/h comme ceux observés lors du cyclone tropical Patricia en 2015 dans l'Atlantique nord. Les conséquences de la formation d'un système cyclonique peuvent être également maritimes. En effet, de longues houles ou encore des ondes de tempête, c'est-à-dire des surélévations anormales du niveau de l'eau, peuvent être générées. Dans sa globalité, un système cyclonique peut s'étendre sur une distance allant jusqu'à 1000km.

Dans le cadre de son programme concernant les cyclones tropicaux, l'Organisation Météorologique Mondiale (OMM) distingue cinq principaux bassins cycloniques à l'échelle du globe : le bassin Atlantique nord, Pacifique central et oriental, comprenant notamment Hawaï, la mer des Caraïbes et le golfe du Mexique. Le bassin nord-ouest Pacifique, le bassin du golfe du Bengale et la mer d'Arabie, le bassin ouest Pacifique et sud-est de l'Océan Indien, ainsi que le bassin sud-ouest de l'Océan Indien.

La source d'énergie principale d'un cyclone est l'eau. En particulier, la température océanique doit être d'au moins 26° Celsius en moyenne dans les 60 premiers mètres de profondeur pour identifier la formation d'un cyclone tropical. Une conjonction de facteurs liant, entre autres, la pression atmosphérique ainsi que la température de l'eau peut aller de pair avec une intensité cyclonique plus ou moins grande. Ainsi, l'intensité d'un cyclone tropical peut être caractérisée par le niveau de pression atmosphérique en son centre, sa taille, la hauteur de l'onde de tempête générée, voire sa durée d'existence. Dans cette thèse, comme dans la plupart des évaulations d'impact cyclonique, nous nous référerons essentiellement à l'intensité comme la vitesse des vents tourbillonnants soutenue au cours d'une minute (Felbermayr & Gröschl, 2014 ; Hsiang & Jina, 2014 ; Krichene & al. 2021). En fonction de cette dernière donnée, un cyclone tropical peut être qualifié de différentes manières :

- on parle de dépression tropicale, si la vitesse constatée est inférieure à 63 km/h ;
- entre 63 et 117 km/h, il s'agit d'une tempête tropicale ;
- au-delà de 117 km/h, on parle de cyclone tropical. Cependant, cette appellation peut varier d'une région à une autre : on emploie le terme d'ouragan en Atlantique nord et Pacifique nord-est, ou de typhon dans le Pacifique nord-ouest.

Selon le bassin de cyclone tropical, la classification des phénomènes ayant une intensité supérieure à 117 km/h peut varier. Par exemple, celle des ouragans est décrite par l'échelle de Saffir-Simpson qui est scindée en cinq catégories. Dans le Pacifique nord-ouest, on parle de « super typhon » lorsque la vitesse des vents soutenus dépasse 244 km/h.

Afin d'assurer le suivi des phénomènes cycloniques, l'OMM s'appuie sur six centres météorologiques régionaux spécialisés (CMRS) situés au cœur de ces bassins, notamment à Miami (Etats-Unis) pour couvrir l'Atlantique nord et le Pacifique nord-est, Tokyo (Japon) pour le Pacifique nord-ouest, Honolulu (Etats-Unis) pour le Pacifique central, New-Delhi (Inde) pour le golfe du Bengale et la mer d'Arabie, à Nadi (Fidji) pour le Pacifique sud-ouest, et enfin, à Saint-Denis de La Réunion (France) pour une veille cyclonique dans le sud-ouest de l'Océan Indien. Suite à une cyclogenèse, l'une des missions principales de ces centres est de prévoir la trajectoire et les variations en intensité des cyclones formés. Pour cela, les CMRS s'appuient sur des modèles de prévision. Si diverses méthodes d'observation telles que les radiosondages, les avions chasseurs de cyclones, les images radar ou satellitaires existent, les CMRS n'ont la capacité de simuler l'évolution des cyclones avec finesse uniquement dans la limite de 24 heures. Au-delà de ce seuil, ces derniers font référence à des tendances. L'anticipation des trajectoires et des intensités cycloniques est d'autant plus importante que ces phénomènes peuvent avoir une durée de vie allant jusqu'à cinq semaines comme le cyclone Freddy en 2023 dans le sud-ouest de l'Océan Indien, ou parcourir d'importantes distances comme l'ouragan John, qui a parcouru plus de 13000 km à travers le Pacifique en 1994. Au cours de leur progression, les cyclones tropicaux sont susceptibles de traverser des environnements humains, et donc, d'entrainer des conséquences économiques. Ceci constitue l'objet de cette thèse de doctorat. En particulier, nous nous focaliserons sur les conséquences macroéconomiques, c'est-à-dire sur les grands agrégats des systèmes économiques.

De tout temps, les impacts des cyclones tropicaux sur les systèmes économiques ont été observés par l'Homme, notamment à travers les dommages causés sur leur environnement immédiat. Ces impacts sont, par ailleurs, voués à être accentués du fait du dérèglement climatique. En effet, les rapports du GIEC (2019 ; 2022) ou d'autres travaux de recherche académiques (Knutson & al., 2010) alertent sur l'augmentation à venir dans l'intensité des phénomènes à l'échelle mondiale, mais également de l'extension des zones de cyclogenèse. De manière générale, les pertes dues aux catastrophes naturelles peuvent être classées en deux catégories. Tout d'abord, on retrouve les pertes directes, qui, très intuitivement, correspondent aux dommages infligés lors du passage du cyclone tropical par un territoire donné. En l'occurrence, outre la dégradation environnementale engendrée, il s'agit des dégâts infligés aux logements, aux propriétés des entreprises, à la production - notamment agricole -, aux infrastructures publiques telles que les routes, les réseaux d'eau ou d'électricité. Les pertes directes peuvent aussi être humaines, car le nombre de décès ou de blessés, ou tout simplement le choc émotionnel provoqué par un épisode cyclonique est souvent conséquent (Botzen & al., 2019). D'après l'OMM, les cyclones tropicaux seraient responsables de la mort de plus de 700 000 personnes au cours des 50 dernières années. La seconde catégorie correspond aux pertes indirectes, définies par Camargo & Hsiang (2016) comme étant l'ensemble des ajustements dans les comportements et ainsi que les décisions économiques faisant suite à l'occurrence d'une catastrophe. Kousky (2014) recense dans cette catégorie toutes les pénuries d'électricité ou d'eau, les interruptions d'activité et autres chocs en cascade du fait d'une rupture dans la chaine de production, l'impact sur l'utilité des agents économiques du fait d'une qualité de vie dégradée (allongement des temps de transports, infrastructures sanitaires défaillantes etc.), et tout autre impact de long-terme sur la santé des populations.

Si la liste des pertes économiques peut être très longue, les retombées positives amorcées par la reconstruction post-catastrophe vient semer le doute quant à un avis préalablement tranché sur un impact économique globalement négatif des catastrophes naturelles. Cette dernière remarque permet de nourrir de nombreuses réflexions épistémologiques sur notre sujet de thèse. Par exemple, on peut évoquer le sophisme de la vitre brisée (Bastiat, 1869). La destruction des biens matériels générée par la catastrophe constituerait, selon certains auteurs, une opportunité économique et entrainerait un regain d'activité (Skidmore & Toya, 2002 ; Crespo Cuaresma & al., 2008). Dans ce contexte, cette thèse aborde la problématique de l'impact économique des cyclones tropicaux par une revue de littérature approfondie sur le sujet, une discussion sur les indicateurs de mesure d'intensité cyclonique ainsi que quelques statistiques descriptives sur nos données cycloniques. Viennent ensuite deux évaluations d'impact de ces phénomènes sur la croissance économique à différentes échelles géographiques, où les effets mondiaux jusqu'aux effets locaux sont examinés. Enfin, dans un dernier chapitre, les effets sur la répartition des revenus au sein de la population américaine est explorée.

Chapter 1

Background discussion

Written in French

1.1 Revue de littérature

La littérature sur les conséquences économiques des cyclones tropicaux est un sous-ensemble de la littérature sur les catastrophes naturelles, qui est très vaste et qui met en exergue des résultats aussi divers que contradictoires. Cette absence de réponse tangible et univoque fait appel à davantage de recherche sur le sujet.

1.1.1 Des résultats disparates

Tout d'abord, on y retrouve des conclusions sur un effet positif des catastrophes naturelles. Albala-Bertrand (1993) étudie les effets de 28 catastrophes naturelles survenues dans 26 pays durant la période 1960-1979 sur la croissance du PIB ou le taux d'inflation sur un court-terme, *i.e.*, 3 ans après l'occurrence de la catastrophe. L'analyse des fluctuations statistiques de ces variables pré- et post-catastrophe révèle un effet positif sur la croissance économique. En revanche, aucun effet inflationnaire n'est décelé. Skidmore & Toya (2002) explorent les effets de long-terme des catastrophes naturelles dans 89 pays entre 1960 et 1990. En distinguant les catastrophes géologiques (séismes, éruptions volcaniques, explosions naturelles, avalanches, ou glissements de terrain) des catastrophes climatiques (inondations, cyclones, pluies verglaçantes, tempêtes de neige ou tornades), cet article met en avant une corrélation positive entre le taux de croissance du PIB et la fréquence de catastrophes climatiques. Cette relation positive s'explique par un renforcement du capital humain et de la productivité globale des facteurs en réponse au choc. En considérant un échantillon de pays en développement entre 1976 et 1990, Crespo Cuaresma & al. (2008) estiment les effets des catastrophes naturelles sur un indicateur de recherche et développement. Les pays ayant un niveau de développement relativement élevé bénéficieraient d'une absorption technologique grâce à leurs importations depuis les pays développés. En somme, ces trois articles corroborent des phénomènes de destruction créatrice à la Schumpeter. Les catastrophes naturelles constituent une opportunité afin de se rééquiper en technologies nouvelles et plus performantes. *A contrario*, d'autres articles soulignent un effet négatif. Ces études montrent que les catastrophes naturelles sont un frein pour la croissance économique, et les dommages infligés empêchent le développement économique des pays. Hochrainer (2009) se focalise sur 225 catastrophes naturelles ayant toutes causées des pertes excédant 1 % du PIB et détermine des effets négatifs sur le PIB perceptibles jusqu'à 5 ans en comparaison d'une situation où la catastrophe n'aurait eu lieu. Felbermayr & Gröschl (2014) concluent sur un impact globalement négatif des catastrophes naturelles sur la croissance économique. Cet effet négatif est principalement porté par les séismes et les catastrophes météorologiques telles que les cyclones ou les inondations. En outre, des effets non-linéaires sont estimés selon l'intensité de la catastrophe. Les pays plus démocratiques, et ceux plus ouverts aux échanges commerciaux accusent de moindres pertes de croissance économoque. Enfin, de nombreuses études démontrent que les effets sont contrastés. Les pays développés ou les larges territoires sont plus à même de résister aux externalités macroéconomiques provoquées par les catastrophes naturelles que leurs homologues en développement ou plus petits (Noy, 2009). En exploitant un panel de 196 pays entre 1970 et 2008, Cavallo & al. (2013) estiment un impact négatif des catastrophes naturelles intenses sur la croissance économique à l'échelle mondiale. En revanche, ce résultat perd toute significativité statistique lorsque l'on retire de l'échantillon initial des observations où, lors de la même période, d'autres évènements ont suscité une grande agitation sociale comme la révolution des sandinistes au Nicaragua, ou la révolution islamique en Iran en 1979. La disparité des effets sur la croissance économique repose aussi sur les aspects sectoriels. Loayza & al. (2012), désagrègent les résultats obtenus sur 94 pays entre 1961 et 2005 selon le niveau de développement, et comparent l'impact sur le secteur agricole avec celui sur les autres secteurs. Leurs conclusions se résument à un impact négatif plus important lorsqu'il s'agit d'un évènement intense, à plus forte raison dans les pays en développement. L'effet des sécheresses et des cyclones sur le secteur agricole est négatif, mais celui d'inondations est positif sur ce secteur ainsi que sur le secteur tertiaire. Les résultats sur le secteur secondaire sont non-significatifs. Fomby & al. (2013) confirment ces derniers résultats dans une étude de 84 pays sur la période 1960-2007. Les inondations modérées ont un effet positif sur la croissance du secteur agricole quel que soit le niveau de développement du pays. Dans les pays développés, seul le secteur agricole est négativement impacté par les sécheresses, mais cet effet annihilé à terme. En utilisant un panel de 113 pays observés pendant 36 ans, Jaramillo (2009) expose le fait que l'impact sur la croissance économique diffère selon le niveau d'incidence de la catastrophe. Dans le cas de catastrophes ayant causé des dégâts mineurs, l'effet immédiat des catastrophes naturelles est positif, et se dissipe après quelques années. Pour ceux dont l'incidence est modérée, l'effet du nombre de décès dû à la catastrophe est négativement lié à la croissance économique, et le taux de décès à la suite de phénomènes extrêmes est corrélé positivement avec la croissance économique.

En somme, les principaux arguments avancés dans la littérature pour expliquer les effets positifs sont relatifs à une meilleure productivité marginale de la capital du fait des dommages causés, ou a un effet de substitution du capital. Une autre source d'explication provient également des aides publiques au développement, qui soutiennent la croissance jusqu'à un certain point dans le court-terme. Les effets négatifs s'expliquent quant à eux par l'affaiblissement des capacités de production. Malgré les politiques de relance mises en place post-catastrophes, les perspectives de croissance ne parviennent pas à atteindre celles anticipées en l'absence de la catastrophe. Par ailleurs, la contraction de l'activité économique implique une diminution des recettes gouvernementales à travers les taxes. Selon Klomp & Valckx (2014), les résultats opposés dans la littérature s'expliquent principalement par le type de catastrophe naturelle étudié, ou les choix relatifs à l'échantillonnage, l'horizon temporel, la spécification ou l'estimateur. Par le biais d'une méta-analyse reprenant plus de 750 résultats de la littérature sur les liens entre catastrophes naturelles et croissance économique, ces derniers concluent sur un effet globalement négatif. Ils reportent également un biais dans les publications, favorisant les résultats négatifs et significatifs. Afin de synthétiser les résultats déjà établis, Hsiang & Jina (2014) dressent quatre principaux scénarios concernant les perspectives à long-terme d'une économie affectée par une catastrophe naturelle :

- « Destruction créatrice » : l'impact est positif dès la fin de la catastrophe. L'économie est relancée par l'augmentation de la demande de biens et de services par la population en proie à remplacer le capital physique détruit.

- « Reconstruire mieux » : les conséquences de court-terme sont négatives, du fait des pertes humaines et de la diminution du capital productif. Cependant, le remplacement du capital détruit avec des équipements plus modernes et performants sont susceptibles d'entraîner des effets positifs sur le long-terme. Les catastrophes naturelles sont vues ici comme une « opportunité » de pouvoir innover.

- « Reprise jusqu'à la trajectoire initiale » : les effets sur l'activité économique sont négatifs jusqu'à une certaine période, suivi d'une forte reprise due à la hausse de la productivité marginale du capital parallèlement à un déclin du volume de main d'œuvre faisant suite à la catastrophe naturelle. *In fine*, la trajectoire de l'économie rejoint celle qui était la sienne avant la catastrophe. Cette hypothèse fait également intervenir les mécanismes de solidarité économique et de réallocation de budgets inter-régions afin de parvenir à une neutralité des effets sur le long-terme.

- « Pas de reprise » : les effets de court-terme comme de long-terme sont négatifs. A la suite d'une catastrophe naturelle et la destruction du capital physique, les fonds mobilisés lors de la phase de reconstruction substituent d'autres investissements productifs qui auraient eu lieu en l'absence de la catastrophe. L'utilité marginale liée à la consommation supplante alors celle de l'investissement (Anttila-Hughes & Hsiang, 2011) et la trajectoire de l'activité économique reste inférieure à celle prévue en l'absence de la catastrophe de façon permanente.

En ce qui concerne les liens entre cyclones tropicaux et croissance économique, les résultats les plus récents tendent à valider l'hypothèse de pertes intertemporelles voire permanentes (Hsiang & Jina, 2014 ; Kunze, 2021 ; Krichene & al., 2021). Il est important d'ajouter que toute cette littérature s'inscrit parmi celle sur l'effet des catastrophes macroéconomiques rares, au sens de Barro & Ursúa (2012). Les stratégies économétriques adoptées pour évaluer ces chocs macroéconomiques de court-terme sont analogues à celles relevant de notre problématique. On peut inclure dans cette catégorie les chocs de politique fiscale, monétaire, d'emploi, les conflits armés, les chocs boursiers ou commerciaux.

1.1.2 Pluralité des variables dépendantes

De ce qui précède, nous comprenons qu'au-delà des conséquences sur la croissance économique, beaucoup de travaux de recherche traitent des incidences directes ou indirectes induites par la catastrophe. Crespo Cuaresma (2010), Sacerdote (2012) ou encore Imberman & al. (2012) étudient les effets sur l'éducation, respectivement sur l'accumulation du capital humain, sur la performance scolaire et les effets de pairs induits par un changement d'établissement scolaire du fait d'une catastrophe. Concrètement, Crespo Cuaresma (2010) montre une corrélation négative entre le risque de catastrophe naturelle et le taux de scolarisation dans le secondaire. Ce lien est porté par les catastrophes géologiques. Sacerdote (2012) examine les performances scolaires de long-terme et l'accès aux études supérieures des victimes des ouragans Katrina et Rita aux Etats-Unis en 2005. Les résultats scolaires des élèves ayant été contraints de changer d'établissement scolaire diminue sur un court-terme mais s'améliore progressivement après quelques années selon les comtés. Aucun effet significatif n'apparaît quant au nombre d'entrées à l'université des victimes. Imberman & al. (2012) travaillent sur les mêmes évènements que Sacerdote (2012), et montrent l'absence d'effet sur la réussite scolaire dans les établissements ayant accueilli les évacués de Katrina et Rita. L'afflux de victimes a cependant provoqué une hausse de l'absentéisme et des problèmes disciplinaires dans le secondaire à Houston. Deryugina & Molitor (2020) étudient les conséquences sur la santé des victimes de Katrina vivant initialement à la Nouvelle-Orléans. L'espérance de vie des populations déplacées s'est allongée. Cet effet positif s'explique par l'émigration vers des territoires en moyenne plus riches, ayant un plus faible taux de mortalité et une meilleure hygiène de vie. Entre autres, cette étude met en lumière l'effet causal de la position géographique sur la mortalité des individus. Belasen & Polachek (2008) étudient les effets des ouragans sur le marché du travail en Floride, et plus particulièrement sur le taux d'emploi et le salaire des travailleurs. Tous secteurs confondus, les phénomènes cycloniques font chuter le taux d'emploi, et entraînent un salaire par tête plus élevé. Une décomposition des effets sectoriels montre que le secteur de la construction se redynamise à la suite d'une catastrophe. Les revenus dans les secteurs financiers, des transports ou manufacturier diminuent dans les territoires impactés. Deryugina (2017) étudie les ouragans ayant affecté les Etats-Unis entre 1979 et 2002, et les effets observés 10 ans avant jusqu'à 10 ans après l'occurrence de telles catastrophes sur les finances publiques. L'estimation des coûts directs, captés notamment avec le flux d'aide publique liée à la catastrophe, et indirects, c'est-à-dire les transferts sociaux comme la sécurité sociale ou l'assurance chômage, montre la persistance d'effets sur la fiscalité des Etats-Unis, effets qui dépassent largement le périmètre des dépenses directes liées à la catastrophe. Les implications sociologiques d'une catastrophe naturelle comme celles sur le niveau de confiance global est exploré par Toya & Skidmore (2014). Dans une étude portant sur 146 pays entre 1984 et 2004, ces derniers montrent que les catastrophes naturelles sont positivement corrélées avec le niveau de confiance entre les individus dans un même pays. Plus ou moins en lien avec cette thématique, Escaleras & al. (2007) étudient les conséquences des séismes en termes de corruption dans le secteur public. En étudiant 344 épisodes sismiques entre 1975 et 2003, un lien positif entre corruption dans le secteur public et le nombre de décès à la suite d'une catastrophe est démontré. Les études faisant le lien entre catastrophes naturelles et inégalités existent également. Sur base monde, Yamamura (2015) met en exergue une augmentation des inégalités de revenus dans les 5 années qui suivent une catastrophe naturelle, et une absence d'effet au-delà de cet horizon temporel. Keerthiratne & Tol (2018) étudient la même problématique dans le cas du Sri Lanka entre 1990 et 2013. Les catastrophes naturelles seraient, cette fois-ci, bénéfiques aux inégalités de revenus. Cependant, ce résultat doit être mis en perspective avec le fait que les catastrophes font baisser les inégalités de revenus tirés d'activités non-agricoles et agricoles non-saisonnières, mais accroissent celles liées aux revenus agricoles saisonnières. Et, les populations plus riches sont bien moins représentées dans cette dernière catégorie. Enfin, Kahn (2005) étudie l'influence de la qualité des institutions ou de la géographie sur les incidences d'une catastrophe naturelle. En moyenne, les pertes humaines tendent à être réduites pour les pays dotés d'institutions plus performantes, et certains continents sont plus exposés que d'autres : les pays d'Asie et d'Amérique recensent plus de victimes d'une catastrophe naturelle que ceux du continent africain.

1.1.3 Différentes méthodologies

Outre le choix de la question de recherche, les études existantes se distinguent les unes des autres selon différents axes. Tout d'abord, le choix de l'horizon temporel. Lorsque certaines analyses portent sur les conséquences de court-terme, d'autres articles examinent les impacts de moyen-terme voire de long-terme (Hsiang & Jina, 2014). Paxson & Rouse (2008) examinent les déterminants d'un retour à la Nouvelle-Orléans dans les 18 mois qui ont suivi l'ouragan Katrina pour les populations évacuées. Felbermayr & Gröschl (2014) mesurent l'impact des catastrophes naturelles sur la croissance économique à horizon de 5 ans, et Hsiang & Jina (2014) étudient la même question sur 20 ans. Certains articles optent donc pour l'étude d'un évènement en particulier comme l'ouragan Katrina en 2005 (voir également Imberman & al., 2012 ; Sacerdote, 2012 ; Deryugina & Molitor, 2020), et d'autres sur une série d'évènements, de nature différentes ou non, au sein d'un même pays ou de plusieurs pays. Ensuite, de nombreuses méthodologies d'évaluation existent. Skidmore & Toya (2002) exploitent des données en coupe afin d'estimer les effets des catastrophes naturelles sur la croissance économique de long-terme à travers des modèles de régression linéaire standards. Crespo Cuaresma (2010) exploite une technique de modélisation bayésienne (« *Bayesian Model Averaging* »), afin de sélectionner judicieusement les variables de contrôle pertinentes et nécessaires à l'analyse. Kahn (2005) utilise un modèle binomial négatif à inflation de zéro pour établir une relation entre le nombre de décès provoqués par une catastrophe naturelle, dont la dispersion est conséquente, et la richesse d'un pays. Il utilise également un modèle probit pour étudier les liens entre la probabilité d'occurrence d'une catastrophe naturelle et des paramètres géographiques. Cavallo & al. (2013) construisent un groupe de contrôle synthétique à partir de la méthode développée dans Abadie & Gardeazabal (2003) et ainsi obtenir un contrefactuel approprié à l'étude des conséquences sur la croissance économique. Loayza & al. (2012), recourent à la méthode des moments généralisés en système pour traiter la même question de recherche, en proposant toutefois une décomposition sectorielle approfondie de l'impact. Strobl (2011) met en exergue l'importance des effets spatiaux dans l'étude des effets des ouragans sur la croissance économique aux Etats-Unis, et utilise à ce titre des modèles de régression avec corrélation spatiale des erreurs. Krichene & al. (2021) portent une considération particulière aux phénomènes sociaux décorrélés des catastrophes naturelles et exploitent une méthode de régression linéaire robuste aux valeurs extrêmes pour estimer l'impact des cyclones et des inondations fluviales sur la croissance économique des pays. Afin d'étudier l'interdépendance entre plusieurs variables économiques endogènes, Raddatz (2007 ; 2009), Fomby & al. (2013) ou encore Mohan & al. (2018) utilisent des modèles vectoriels autorégressifs avec variable exogène (VARX). La plupart des méthodes citées dans ce paragraphe ne sont qu'une variante de régressions de données de panel avec prise en compte des effets fixes, qui demeure la méthode la plus couramment utilisée (Jaramillo, 2009 ; Felbermayr & Gröschl, 2014 ; Hsiang & Jina, 2014 ; Kunze, 2021). Dans l'ensemble, les obstacles dans les estimations économétriques sont relatifs au traitement des valeurs extrêmes - notamment de la variable dépendante -, aux effets spatiaux, à la période d'échantillonnage, et à l'utilisation de contrefactuels pertinents. Dans les chapitres suivants, nous nous efforçons de tenir compte de ces problématiques en proposant des stratégies d'estimations différentes, et ce, malgré les limites rencontrées dans la disponibilité des données. Ce dernier point explique pour partie le choix d'études de cas portant sur les Etats-Unis plutôt qu'un autre territoire. Le tableau 1.1 présente une synthèse des éléments clés des articles mentionnés dans cette section sur les catastrophes naturelles. Le tableau 1.2 résume ceux portant spécifiquement sur les cyclones tropicaux.

1.2 Diversité des données et des indicateurs

1.2.1 Indicateurs économiques

Ce qui constitue probablement la source d'hétérogénéité la plus cruciale entre ces travaux correspond au choix des données, et *a fortiori* de l'indicateur, sur les catastrophes naturelles. A notre connaissance, la quasi-totalité des papiers avant 2010 exploitent des indicateurs dits « basés sur des paramètres économiques », tels que le nombre de décès dus à une catastrophe naturelle, ou bien les coûts totaux liés aux dommages infligés etc. Skidmore & Toya (2002) utilisent le nombre total de catastrophes rapporté à la taille du pays lorsque Kahn (2005) choisit le logarithme de 1+ le nombre total de décès. Yamamura (2015) utilise le nombre total de catastrophes au cours d'une année. Noy (2009) utilise trois indicateurs différents : le nombre de personnes tuées, le nombre de victimes, et le montant des dommages directs, chacun sont rapportés au mois de l'année où la catastrophe a eu lieu afin de tenir compte des effets de temporalité. Pour affiner davantage les indicateurs selon l'intensité des phénomènes, Loayza & al. (2012) emploient le logarithme du nombre de victimes rapportée à la population totale. Le nombre de victimes est composé du nombre de blessés ainsi que du nombre de personnes décédées, avec le nombre de blessés pondéré par 0,3. Fomby & al. (2013) s'inspirent de cet indicateur, et somment le nombre total d'évènements pour lesquels le nombre total de décès et 30 % du nombre total de blessés rapportés à la population totale soit supérieur à 0.0001. Ces derniers étudient ensuite spécifiquement les évènements intenses, en se restreignant aux évènements où ce ratio est strictement supérieur à 0.01. Comme mentionné précédemment, Hochrainer (2009) se restreint aux évènements de grande ampleur, définis comme ceux ayant engendré des dégâts dépassant 1 % du PIB total du pays. Les problèmes d'endogénéité derrière le choix de tels indicateurs ont été démontrés entre autres par

Table 1.1: Synthèse des résultats de la littérature sur les conséquences économiques des catastrophes naturelles

Article	Thématique	Echelle	Horizon temporel	Stratégie d'estimation	Résultats principaux
Albala-Bertrand (1993)	Croissance économique	Base monde	Court-terme	Statistiques descriptives	Effet positif
Cavallo & al. (2013)	Croissance économique	Base monde	Long-terme	Moindres carrés	Effets negatifs Aucun effet sans valeurs extrêmes.
Crespo Cuaresma & al. (2008)	R&D	Pays en développement	Court-terme	Moindres carrés	Effet positif pour les plus aisés
Crespo Cuaresma (2010)	Education	Base monde	Court-terme	Modélisation bayesienne	Effet négatif scolarisation
Escaleras & al. (2007)	Sociologie	Base monde	Court-terme	Moindres carrés	Effet négatif sur corrpution secteur public
Felbermayr & Gröschl (2014)	Croissance économique	Base monde	Moyen-terme	Moindres carrés	Effet négatif
Fomby & al. (2013)	Croissance économique	Base monde	Court-terme	Panel VARX	Effet négatif sécheresses Effet positif inondations
Hochrainer (2009)	PIB	Base monde	Moyen-terme	ARIMAX	Effet négatif
Jaramillo (2009)	Croissance économique	Base monde	Court-terme	Moindres carrés	Effet positif si incidences mineures Effet négatif si incidences modérées Effet positif si incidences majeures
Keerthiratne & Tol (2018)	Inégalités	Sri Lanka	Court-terme	Moindres carrés	Effet bénéfique
Kahn (2005)	Institutions/Géographie	Base monde	Court-terme	Moindres carrés	Effet bénéfique institutions/richesse sur pertes humaines
Loayza & al (2012)	Croissance économique	Base monde	Moyen-terme	MMG en système	Effet négatif cyclones et sécheresses Effet positif inondations
Noy (2009)	Croissance économique	Base monde	Court-terme	Moindres carrés	Effet négatif. Amoindri pour les plus aisés.
Raddatz (2007)	Croissance économique	Base monde	Long-terme	Panel VARX	Effet négatif catastrophes climatiques
Raddatz (2009)	Croissance économique	Base monde	Long-terme	Panel VARX	Effet négatif
Skidmore & Toya (2002)	Croissance économique	Base monde	Long-terme	Moindres carrés	Effet positif
Toya & Skidmore (2014)	Sociologie	Base monde	Court-terme	Moindres carrés	Effet positif niveau de confiance
Yamamura (2015)	Inégalités	Base monde	Long-terme	Moindres carrés	Effet négatif moyen-terme

Kahn (2005) : le nombre de décès causés par une catastrophe naturelle est lié aux conditions de développement du pays impacté.

La plupart des études faisant usage de ce type d'indicateur exploitent la base de données EM-DAT, de l'Université Catholique de Louvain, qui est une base de données déclarative niveau « événement-pays », et dont les observations sont sélectionnées selon une correspondance avec l'un au moins des critères suivants : au moins 10 personnes ont été déclarées comme tuées par la catastrophe, 100 personnes ou plus ont été blessés, une aide internationale a été requise, ou une situation d'état d'urgence a été déclarée par le gouvernement en place.

Une autre base de données similaire, NatCatSERVICE, existe également. Elle est développée par la compagnie d'assurance MunichRE, et est utilisée entre autres dans Hochrainer (2009). Le fait que la présence d'une observation dans l'EM-DAT soit conditionnée par l'un des critères précédents est critiquable. La plupart des pays développés accusent souvent un fort taux de dommages mais peu d'incidences d'un point de vue humain. Ils se retrouvent donc souvent mécaniquement exclus de la base, ou du moins, sous-représentés. En effet, les « grands » pays – en termes de superficie ou de développement – possèdent davantage de moyens pour dissiper les effets néfastes d'une catastrophe naturelle. Leur capacité d'absorption des chocs est supérieure à celle des autres pays (Cavallo & Noy, 2010). Par ailleurs, Hoeppe (2016) montre que le niveau de richesse d'un

Table 1.2: Synthèse des résultats de la littérature sur les conséquences économiques des cyclones tropicaux

Article	Thématique	Echelle	Horizon temporel	Stratégie d'estimation	Résultats principaux
Belasen & Polachek (2008)	Marché du travail	Etats-Unis (Floride)	Court-terme	Moindres carrés	Baisse de l'emploi Hausse du salaire par tête
Deryugina (2017)	Finances publiques	Etats-Unis	Long-terme	Moindres carrés	Effet négatif
Deryugina & Molitor (2020)	Santé	Etats-Unis	Long-terme	Moindres carrés	Espérance de vie allongée
Felbermayr & Gröschl (2014)	Croissance économique	Base monde	Moyen-terme	Moindres carrés	Effet négatif
Hsiang & Jina (2014)	Croissance économique	Base monde	Long-terme	Moindres carrés	Effet négatif
Imberman & al. (2012)	Education	Etats-Unis	Court-terme	Moindres carrés	Hausse absentéisme et problèmes disciplinaires à Houston
Krichene & al. (2021)	Croissance économique	Base monde	Long-terme	Moindres carrés	Effet négatif
Kunze (2021)	Croissance économique	Base monde	Court-terme	Moindres carrés	Effet négatif
Mohan & al. (2018)	Déterminants PIB	Base monde	Caraïbes	Long-terme	Effet négatif exportations, consommation Effet positif investissement, importations dépenses publiques
Paxson & Rouse (2008)	Décision/Comportement	Base monde	Long-terme	Moindres carrés	Victimes d'inondations moins susceptibles de revenir à la Nouvelle-Orléans.
Sacerdote (2012)	Education	Etats-Unis	Long-terme	Moindres carrés	Effet négatif court-terme Effet positif long-terme selon comté

pays est positivement corrélé avec le niveau de dommages infligé aux propriétés. En revanche, le lien est négatif avec les décès et les impacts sur la croissance économique sont moindres.

1.2.2 Indicateurs physiques

Par opposition à ces indicateurs souffrant de biais de sélection intrinsèques - ce qui est démontré par Felbermayr & Gröschl (2014) - il existe des données dites « physiques ». Celles-ci recensent l'intensité d'un phénomène de catastrophe naturelle selon des mesures biophysiques. Par exemple, l'intensité d'un séisme va être exprimée en échelle de Richter, un phénomène de sécheresse peut être mesuré selon le nombre de jours avec une température supérieure d'un écart-type aux normales de saison. En particulier, l'intensité des phénomènes cycloniques peut être mesuré par l'énergie dissipée par le cyclone, ou bien la vitesse des vents de progression. La nécessité de prendre en compte des données physiques a pour la première fois été discutée par Noy (2009) : « le problème d'exogénéité peut potentiellement être dépassé en construisant un indicateur de l'intensité de la catastrophe qui dépend uniquement des caractéristiques physiques de la catastrophe ». Ceci a fait émerger plusieurs études utilisant ce type de mesure. On peut citer, par exemple, Hsiang (2010) utilise l'énergie dissipée par le cyclone, mesurée en m^3/s^2 pour faire le lien entre activité économique et phénomènes cycloniques dans le bassin Caraïbes. L'impact négatif sur le secteur touristique est notamment mis en avant. Felbermayr & Gröschl (2014) étudient différents types de catastrophes naturelles au prisme de leur intensité physique et analysent leurs effets respectifs sur la croissance économique. Ils compilent des données provenant de systèmes d'informations géographiques et exploitent l'échelle de Richter pour obtenir des mesures localisées de l'intensité des séismes. Les éruptions volcaniques utilisent l'index d'explosivité volcanique recensé par le *Global Volcanism Program of the Smithsonian.* L'intensité des phénomènes cycloniques est définie comme le vent maximum ayant été mesuré au sein d'un pays. Les inondations sont mesurées à partir des déviations des niveaux de précipitation par rapport aux tendances mesurées sur le long-terme. Enfin, les sécheresses sont introduites à l'aide d'une variable binaire prenant la valeur 1 si le niveau de précipitation est plus de 50 % en deçà des tendances mesurées sur le long-terme durant trois mois consécutifs lors d'une année donnée, ou si au moins 5 fois dans l'année le niveau de précipitation mesuré est inférieur à 50 % de la normale saisonnière. La base de données GeoMet ainsi construite est disponible en libre accès. Il s'agit d'un panel mondial dont les valeurs couvrent la période 1979-2010. Hsiang & Jina (2014) étudient les liens entre croissance du PIB par habitant et cyclones tropicaux. Ils démontrent l'existence d'un effet négatif de long-terme, *i.e.*, à horizon de 20 ans en employant pour chaque territoire un indicateur de vents soutenus une minute pondéré par la surface totale affectée, ou la population totale exposée. Plus récemment, Zhou et Zhang (2021) mesurent la vitesse moyenne des vents cycloniques à Hong-Kong, rapportée au nombre total d'évènements survenus au cours de l'année. Un autre type d'indicateur biophysique correspond aux proxys de destruction cyclonique. Il s'agit d'indicateurs basés sur des paramètres physiques tels que la vitesse des vents cycloniques et intégrant d'autres paramètres permettant de traduire ces vitesses en pertes économiques. En s'appuyant sur les travaux pionniers d'Emanuel (2005), Strobl (2012) définit un proxy de destruction en élevant la vitesse des vents cycloniques à la puissance 3, puis en pondérant par la population exposée. Les vitesses de vents en dessous 177 km/h sont considérées comme nulles. Mohan & al. (2018) ont recours à un index de dommages f différent, proposé par Emanuel (2011). La fraction des propriétés endommagées est approximée à l'aide d'une fonction de la vitesse des vents cycloniques. Mathématiquement, cela se traduit comme :

$$f_{ijk} = \frac{v_{ijk}^3}{1 + v_{ijk}^3}$$

avec

$$v_{ijk} = \frac{\max\{(V_{ijk} - V_{thresh}), 0\}}{V_{half} - V_{thresh}}$$

Où V_{ijk} correspond à la vitesse maximale ressentie en un point terrestre i, au sein d'un pays k lors du cyclone j. V_{thresh} correspond au seuil en vitesse en dessous duquel on suppose qu'aucun dommage n'aura lieu, et estimé à 92 km/h. Et, V_{half} est défini comme le seuil de vitesse auquel la moitié des propriétés seront endommagées, estimé à 203 km/h. Mohan & al. (2018) obtiennent leur indicateur cyclonique en pondérant cet index de destruction par la population exposée localement.

D'autres études comme celles de Keerthiratne & Tol (2018), ou encore Krichene & al. (2021) utilisent le pourcentage de population exposée. Mais encore, l'idée d'exploiter une variable binaire comme proxy de la catastrophe naturelle est fréquemment observé dans la littérature empirique (Belasen & Polachek, 2008 ; Deryugina, 2017 ; Pleninger, 2022).

La base de données la plus complète et exhaustive en termes de phénomènes cycloniques est la base *International Best Track Archive for Climate Stewardship* (IBTrACS ; Knapp & al, 2010) de l'Agence américaine d'observation océanique et atmosphérique (NOAA). Cette base de données recense l'intensité et la position des phénomènes cycloniques survenus depuis 1950. L'exploitation de ces données à des fins d'évaluations d'impact est limitée par le fait que seules les données sur les trajectoires des centres cycloniques sont disponibles dans cette base de données. Pour obtenir la trajectoire complète des cyclones et leur influence globale au sein des régions exposées, il est nécessaire d'appliquer successivement des modèles de champ de vent développés en météorologie. On retrouve, par exemple, le modèle de Holland (2008), utilisé par Geiger & al. (2018) dans leur base de données *Tropical Cyclone Exposure Database* (TCE-DAT), ou encore le modèle *Limited Information Cyclone Reconstruction and Integration for Climate and Economics* (LICRICE) utilisé par Hsiang & Jina (2014). Strobl (2012) utilise les trajectoires centrales extraites de l'IBTrACS pour ensuite appliquer le modèle de Boose & al. (2004). Ces deux sources de données décrivent les vents cycloniques à une échelle de 0.1° latitude × 0.1° longitude, ce qui correspond à environ 11km^2 lorsque l'on se situe à l'équateur terrestre. Seules les données TCE-DAT sont publiques. Cette base sera utilisée tout au long de cette thèse.

1.2.3 Construction de notre indicateur

L'utilisation de telles données conduit indubitablement à s'interroger sur le choix de la mesure la plus appropriée pour estimer l'impact des cyclones tropicaux. A cet égard, Noy (2009) rappelle que les conséquences d'une catastrophe peuvent dépendre de la taille de l'économie touchée, et donc, l'importance de pondérer les indicateurs physiques par la population totale, ou bien par le niveau de PIB de l'année précédente dans le cas d'un indicateur de dommages. Dans le même esprit, Nordhaus (2006) mentionne la nécessité de se ramener à l'échelle d'un pixel moyen au sein du territoire considéré. Skidmore & Toya (2002) font l'analogie entre la manière de rapporter les indicateurs de catastrophes naturelles à la taille de l'économie - ou de la population considérée - à celle de rapporter le salaire au nombre d'heures travaillées en économie du travail, ou celle de rapporter le PIB au nombre d'habitants en macroéconomie.

A l'aune de ces raisons, dans chacun des articles, nous exploiterons un indicateur de vents pondérés par la part de la population ou de la superficie exposée. Mathématiquement, cette mesure peut s'écrire de la manière suivante :

$$\overline{Cyc}_{i,t} = \sum_{p=1}^{P_i} \max_{s \in \{1,\ldots,S_{p,i,t}\}} \{\text{Vent}_{p,s,i,t}\} \times \text{Pondération}_{p,t} \tag{1.1}$$

avec t l'indice relatif au temps, p désigne un pixel parmi l'ensemble des pixels P_i situés au sein du territoire i. $Vent_{p,s,i,t}$ correspond à la mesure de l'intensité des vents soutenus une minute dans le pixel p, au cours du cyclone s, dans le territoire i au temps t. Enfin, $Pondération_{p,t}$ correspond à la pondération choisie, c'est-à-dire la part de la population ou de la surface que représente le pixel p au sein du territoire i en t. Remarquons qu'à l'instar de Felbermayr & Gröschl (2014), notre indicateur ne retient que la vitesse maximale mesurée pour chaque pixel au cours d'une période temporelle. Ce choix méthodologique est sujet à critique dans le sens où cela entraîne une omission de la fréquence d'occurrence cyclonique dans les estimations. Or, un évènement cyclonique qui succèderait à un autre dans un laps de temps réduit affecterait un territoire dont les sols seraient déjà fragilisés. Un cyclone de faible intensité suffirait potentiellement à provoquer des glissements de terrain par endroits. Ainsi, la répétition de phénomènes cycloniques peut également être délétère pour une économie. Pour pallier cette dimension manquante, l'effet du nombre de cyclones par année est systématiquement estimé en tant qu'analyse de robustesse dans chaque chapitre. Notre indicateur est somme toute assez similaire à celui utilisé par Hsiang & Jina (2014). Toutefois, lors d'estimations des effets de court-terme, nous incluons une pondération par le mois d'occurrence du cyclone, ce qui rend *in fine* notre indicateur original et plus précis que ceux observés par ailleurs dans la littérature.

1.3 Quelques statistiques descriptives

La base TCE-DAT, dont la première extraction a été effectuée en janvier 2021, contient des données sur l'ensemble phénomènes cycloniques survenus entre 1950 et 2015 et ayant affecté un pays au cours de leur trajectoire. La vitesse des vents cycloniques, la population exposée ou encore le nombre d'actifs présents localement sont décrits à un niveau de résolution de 0.1° latitude × 0.1°

longitude à la surface du globe. Une seconde extraction de cette base en mars 2022 demandée spécifiquement auprès des chercheurs de l'Université de Potsdam sur le bassin Atlantique Nord, Pacifique nord et oriental offre une extension des données jusqu'à 2020. Ce second jeu de données a permis la réalisation d'études portant sur les Etats-Unis.

La projection des données de vents au niveau de chaque pixel sur un planisphère met en évidence les différents bassins de cyclones tropicaux mondiaux présentés en introduction générale (Figure 1.1). On observe tout d'abord que les cyclones sont principalement des phénomènes côtiers. L'intensité d'un cyclone s'amenuise mécaniquement lors de la traversée d'un territoire du fait de l'absence d'eau et des forces de frottement. De plus, cette carte fait ressortir les inégalités d'exposition à la fois entre les pays du monde, mais aussi à l'intérieur d'un même pays. Notons que la base TCE-DAT recense des données pour certains pays tels que le Canada, la Norvège, la Nouvelle-Zélande ou des pays de l'Europe de l'ouest, qui se situent au-delà des parallèles délimitant la zone tropicale. Ces pays sont touchés par des cyclones extratropicaux, caractérisés par une structure physique différente. Ces cyclones sont intégrés dans la base uniquement lorsqu'ils sont le fruit d'une transformation d'un cyclone tropical précédent.[1] Les dégâts provoqués et les risques pour les environnements humains étant similaires, nous conservons ces observations lors de nos estimations.

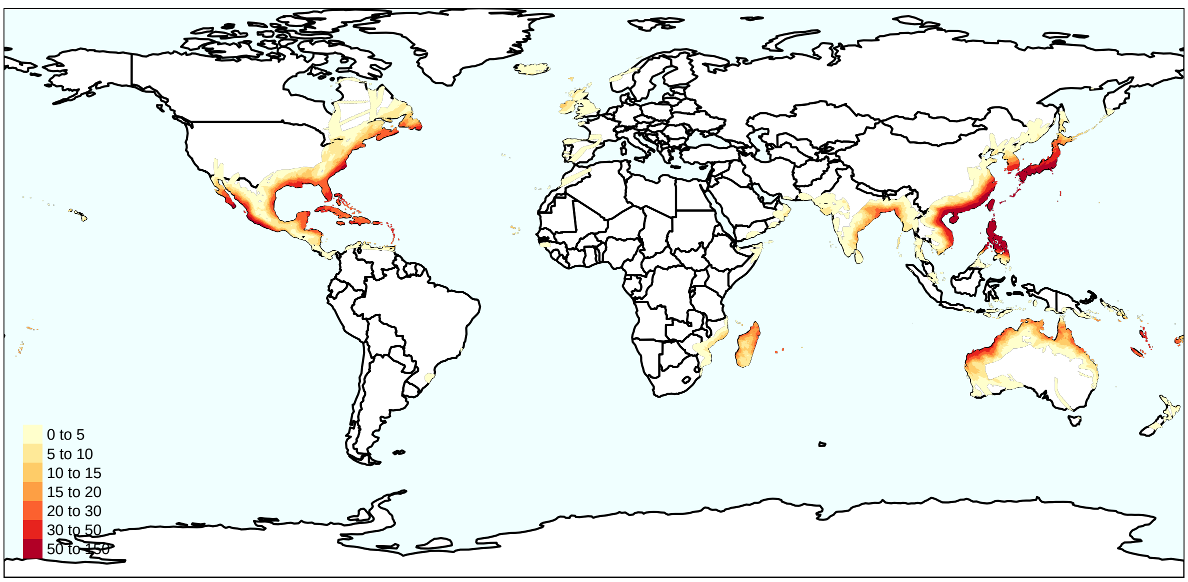


Figure 1.1: Vitesse des vents moyenne annuelle (en km/h) pour chaque pixel terrestre de 0.1° latitude × 0.1° longitude, mesurée entre 1950 et 2015

Les figures 1.2 et 1.3 présentent les corrélations existantes entre l'intensité des phénomènes cycloniques, mesurée à l'aide de notre indicateur sans pondération, et respectivement le PIB par habitant des pays mondiaux et l'ensemble des pays exposés au risque cyclonique. Les données sur

[1]Pour plus d'informations, voir échanges avec Météo France présentés en Annexe Générale A.

le PIB par habitant proviennent des *World Development Indicators* de la Banque Mondiale, et sont actualisées en dollars constants de 2015. Les variables sont calculées en logarithme en moyenne sur la période 1950-2015 pour chaque pays. Lorsque l'ensemble des pays du monde sont intégrés, on observe une grande prévalence de zéros dans la variable cyclonique imputable aux pays non-exposés. Le coefficient de régression linéaire est très faiblement négatif et non significatif. Il existe à la fois des pays développés et fortement exposés tels que le Japon, les Etats-Unis, l'Australie ou Hong-Kong, et des pays en développement avec des niveaux d'exposition comparables tels que les Philippines ou le Mexique. Lorsque les pays non-exposés au risque cyclonique sont ôtés de l'échantillon, la corrélation reste quasiment identique. Ce second graphique affiche toujours la présence de quelques valeurs autour de zéro, qui est principalement expliquée par la faible fréquence d'exposition. Dans l'ensemble, l'intensité des phénomènes cycloniques ne semble donc pas corrélé à la richesse d'un territoire et ces deux graphiques rendent davantage compte des spécificités géographiques dans l'exposition aux cyclones tropicaux comme discuté dans Kahn (2005). Les continents asiatique et américain montrent les niveaux d'intensité les plus élevés, lorsque les pays se situant dans les autres bassins cycloniques font face, en moyenne, à des intensités plus faibles. Toutefois, les cyclones étant des phénomènes très localisés, les fortes valeurs observées pour l'Australie, la Chine ou les Etats-Unis ne rendent probablement pas compte des niveaux d'exposition lorsque l'on considère l'intégralité des territoires de ces pays, d'où l'importance de se ramener à l'échelle d'un pixel moyen au sein d'un pays comme préconisé par Nordhaus (2006). Nous effectuons cela par le biais de pondérations, soit par la part de la surface exposée, soit par la part de la population exposée aux épisodes cycloniques. Dans les deux cas, cela revient à estimer une valeur d'intensité moyenne pour un cyclone si celui-ci touchait de manière homogène tout le territoire d'un pays, ou formulé différemment, si l'intensité moyenne d'un cyclone était mesurée sur une zone aléatoirement choisie au sein d'un pays.

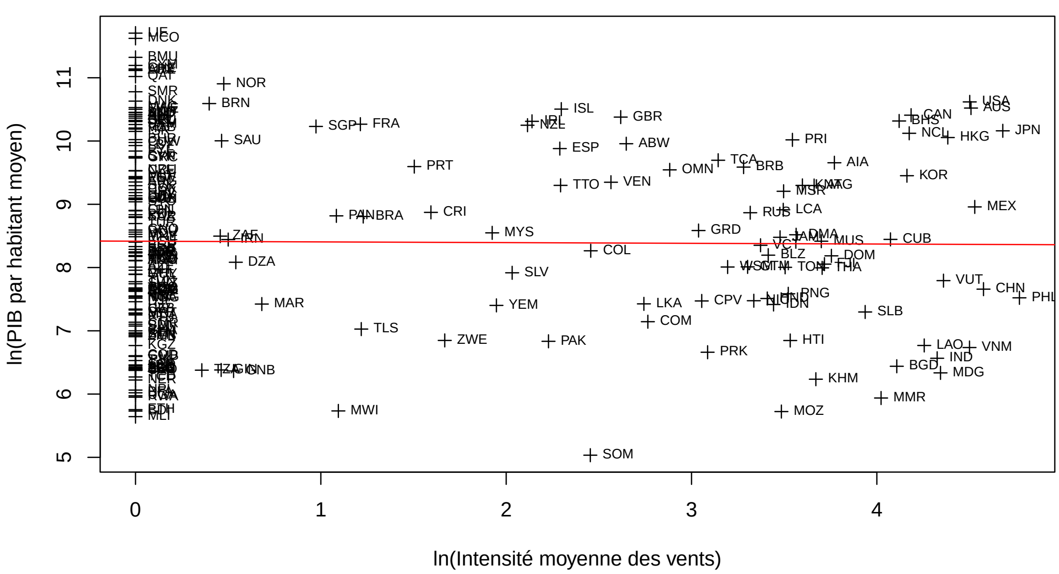


Figure 1.2: Nuage de points et droite de régression entre le logarithme du PIB par habitant moyen et le logarithme de la vitesse moyenne des vents cycloniques pour l'ensemble des pays du monde entre 1950 et 2015

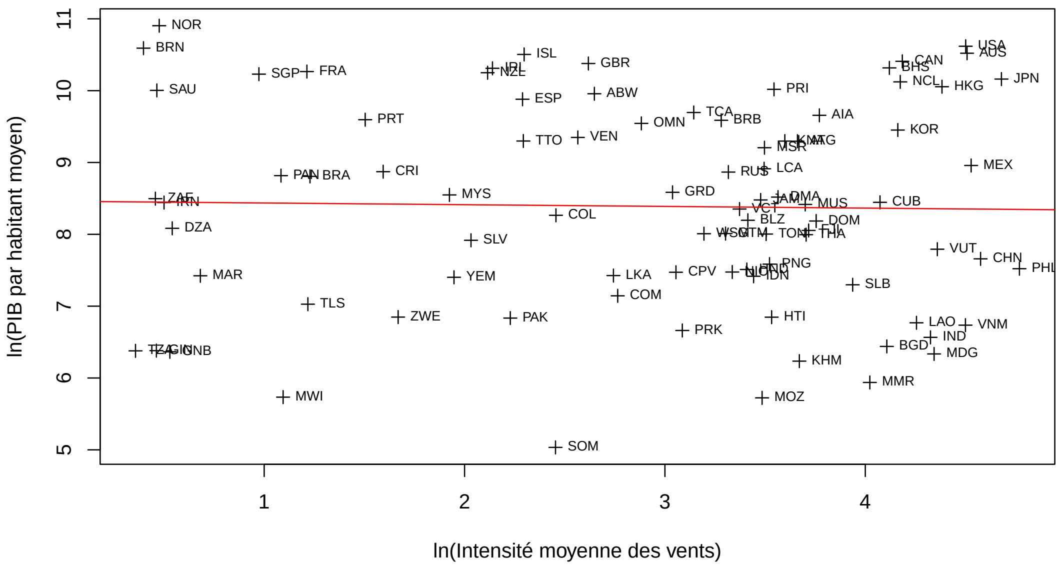


Figure 1.3: Nuage de points et droite de régression entre PIB par habitant moyen et vitesse moyenne des vents cycloniques pour l'ensemble des pays exposés au risque cyclonique dans le monde entre 1950 et 2015

Afin d'obtenir davantage de détails sur l'exposition des pays, le tableau 1.3 présente des statistiques descriptives relatives à notre indicateur cyclonique pour chaque pays entre 1950 et 2015. Pour chaque variable, la médiane est systématiquement à 0 car plus de la moitié des pays du monde ne sont pas concernés par les évènements cycloniques. Toutefois, ce tableau attire l'attention sur la forte dispersion des valeurs, observable par rapport aux écarts-types respectifs des variables. La valeur maximale de 117.8 km/h de moyenne sur la période pour notre indicateur sans pondération est atteinte par les Philippines. Cette valeur maximale est suivie par celles du Japon et de la Chine avec respectivement 107.7 km/h et 97.1 km/h de moyenne. Lorsque l'indicateur intègre une pondération, soit par la superficie totale du pays, soit par la population exposée lors d'un épisode cyclonique, l'amplitude des valeurs est amoindrie, notamment la moyenne qui est presque divisée par deux. La pondération par la part de la population exposée fait davantage baisser les valeurs que la part de la surface exposée. Selon ces deux variables, les Philippines représentent toujours le pays le plus fortement exposé aux cyclones tropicaux, mais l'ajout de pondération bouleverse la suite du classement et place ensuite Hong-Kong, Vanuatu puis le Japon comme pays les plus exposés. Quant au nombre d'évènements cycloniques moyen par année, la Chine est le pays le plus fréquemment touché avec 8 cyclones par an, suivi des Philippines et du Japon avec respectivement 7.4 et 6.8 cyclones par an.

1.4 Structure de la thèse et principaux résultats

La suite de ce manuscrit de thèse se présente comme suit. Le chapitre 2 reprend la question de l'impact des cyclones tropicaux sur la croissance économique, qui constitue une entrée en matière balisée et nécessitant un approfondissement. En effet, les études sur les liens entre cyclones

Table 1.3: Statistiques descriptives

Variable	Pondération	Min.	Max.	Médiane	Moyenne	Ecart-type
$\overline{Cyc}_{i,.}$	Pas de pondération	0	117.8	0	13.2	24.5
$\overline{Cyc}_{i,.}$	Superficie	0	105.3	0	6.8	15.6
$\overline{Cyc}_{i,.}$	Population	0	98.2	0	6.1	13.8
Nombre annuel de cyclones	-	0	8.0	0	0.3	1.1

Notes : Valeurs moyennes intra-pays entre 1950 et 2015. La mesure d'intensité cyclonique est exprimée en km/h. Echantillon mondial composé de 209 pays.

et croissance économique sont les plus nombreuses dans la littérature. Face aux articles déjà cités sur base monde et faisant état d'un impact négatif (Hsiang & Jina, 2014 ; Krichene & al., 2021), Strobl (2011) démontre dans le cas des États-Unis que ces liens ne sont significatifs que lorsque l'on raisonne à l'échelle des comtés ou à l'échelle étatique. En d'autres termes, aux États-Unis, les événements cycloniques ne constituent pas des chocs exogènes suffisamment importants pour être répercutés sur l'activité économique à l'échelle nationale. De surcroît, Zhou & Zhang (2020) estiment que les pertes de croissance observées à Hong-Kong ne sont pas imputables aux dégâts générés par les conséquences météorologiques ou maritimes provoquées par les cyclones, mais plutôt à l'interruption des activités dans le cadre des systèmes d'alertes gouvernementaux. Ainsi, il apparaît clair que les résultats sur base monde dissimulent de l'hétérogénéité. Nous formulons l'hypothèse que l'inégalité d'impact entre les pays est due à deux facteurs : la surface d'exposition au risque cyclonique entraîne davantage de vulnérabilité économique, et le niveau de développement du pays est lié à cette vulnérabilité économique. Par ailleurs, Heger, Julca & Paddison (2008) soulignent le fait que les catastrophes affectent les très petits pays de manière disproportionnée, et sont très souvent exclus des échantillons étudiés.

Tous ces éléments de réflexion conduisent à s'intéresser aux Petits Etats Insulaires en Développement (PEID). Les PEID constituent un groupement de pays reconnu par l'ONU depuis 1992 du fait d'enjeux de développement et environnementaux communs. Lorsque les PEID ont une exposition accrue aux catastrophes naturelles ainsi qu'aux conséquences du changement climatique telles que l'élévation du niveau des mers (GIEC, 2019), ils présentent dans le même temps de nombreuses caractéristiques de vulnérabilité économique. Par exemple, leur faible superficie, leur insularité, leur niveau de production locale naturellement limité et leur éloignement par rapport aux principaux axes commerciaux et/ou aux grandes puissances économiques induisent autant de freins structurels à leur développement ainsi qu'à leur croissance économique.

La distinction de l'échantillon entre PEID et non PEID forme l'originalité de ce premier article. En adoptant une méthode de régression linéaire en données de panel avec prise en compte des effets fixes, nous estimons que des pertes de points de croissance quasiment constantes se cumulent jusqu'à 15 ans après un épisode cyclonique chez les PEID, lorsque l'analyse dans les non PEID demeure non conclusive, et ce, indépendamment du niveau de développement. L'exploration des canaux de transmission derrière les effets négatifs au sein des PEID laisse entrevoir, entre autres, des problématiques en termes d'adaptabilité, d'investissement – de relance post-catastrophe – et une dépendance accrue vis-à-vis des marchés étrangers à la suite d'un évènement cyclonique. En somme, les économies des PEID sont fragilisées par le passage de cyclones tropicaux qui semblent constituer une trappe à pauvreté dans ces pays. Dans une extension de ce second chapitre, nous apportons des analyses complémentaires permettant d'inférer des pertes permanentes de croissance économique.

Les résultats obtenus jusqu'à présent sur base monde semblent donc fortement induits par la présence des PEID au sein des échantillons. Néanmoins, il est important de préciser que cette dernière remarque ne signifie pas qu'un non PEID ne peut être négativement impacté par les phénomènes cycloniques, mais plutôt que, lorsqu'ils sont considérés en tant que groupe de pays, les non PEID ne sont pas significativement impactés par les cyclones. Afin d'étayer davantage cet argument, le chapitre 3 explore les effets des cyclones sur la croissance économique aux Etats-Unis. Les Etats-Unis représentent un cas de figure intéressant dans le sens où il s'agit d'un pays exposé à de nombreuses catastrophes naturelles, et où l'ensemble du territoire n'est pas exposé au risque cyclonique. Pourtant, dans les régions en proie aux cyclones, les dégâts causés peuvent être incommensurables comme lors de l'ouragan Katrina en 2005 qui a infligé aux propriétés des dommages estimés à plus de 100 milliards de dollars (Deryugina & al., 2018).

Ce second article s'inspire grandement de Strobl (2011). Une analyse est proposée à l'échelle des Etats ainsi que des comtés. En utilisant une méthode économétrique similaire, à savoir un modèle de régression à effets fixes avec prise en compte des interactions spatiales, ainsi qu'un jeu de données actualisé, l'intérêt de ce chapitre réside avant tout dans une entière réplicabilité des résultats. Au travers d'estimations sur de nombreux sous-échantillons nationaux – comtés/Etats exposés, côtiers, etc. - nous concluons sur une absence d'effets à la fois à l'échelle étatique et au niveau des comtés lorsque ceux-ci sont échantillonnés au sein du pays dans son intégralité. Toutefois, une seconde partie de l'étude se focalise sur un Etat en particulier, la Floride. Cet Etat est le plus fréquemment exposé aux phénomènes de cyclones tropicaux, mais compte aussi parmi les Etats plus riches et les plus peuplés des Etats-Unis. De plus, les plus grandes métropoles floridiennes comme Miami ou Tempa Bay sont situées le long du littoral, ce qui semble constituer un facteur de vulnérabilité économique supplémentaire. L'utilisation de modèles économétriques de séries temporelles pour les analyses sur la croissance de cet Etat, et toujours de modèles spatiaux pour les comtés floridiens fait ressortir cette fois-ci des résultats négatifs et significatifs de court-terme. Ainsi, ce troisième chapitre démontre l'importance d'examiner les effets régionaux voire localisés dans les analyses en économie de l'environnement. En effet, dans beaucoup de pays, et à plus forte raison dans les non PEID, seules certaines régions soient hautement vulnérables aux phénomènes cycloniques, et la majorité du territoire n'est pas ou peu exposé. Néanmoins, il existe également d'autres pays tels que le Japon ou les Philippines présentant une exposition bien plus homogène au sein de leur territoire.

Les deux premiers articles traitent donc des incidences en termes d'activité économique. Cependant, la croissance économique, définie par exemple comme le taux de croissance du PIB par habitant, ne rend pas compte des conditions de vie de la population, voire de son bien-être. Pour cette raison, la question des inégalités est explorée dans un quatrième chapitre.

Ce chapitre a notamment été motivé par la lecture de Karim & Noy (2016), qui soulèvent le fait que les études sur les impacts directs des catastrophes naturelles doivent aller au-delà d'analyses interpays de la distribution des coûts générés par ces phénomènes ou d'estimations des effets sur l'activité économique, et qu'il serait intéressant d'étudier finement les effets sur la distribution du revenu des ménages. Ainsi, ce dernier article évalue l'impact des cyclones tropicaux sur les inégalités de revenus. Afin de s'inscrire dans la stricte continuité du chapitre précédent, nous conservons les Etats-Unis comme pays d'étude.

Avant toute chose, compte tenu des résultats présentés dans la littérature, il y a plusieurs raisons de penser que les niveaux d'inégalités de revenus aux Etats-Unis peuvent être affectés par les chocs cycloniques. D'une part, Fothergill & Peek (2004) démontrent une plus grande vulnérabilité des populations les plus pauvres face aux catastrophes naturelles aux Etats-Unis, plus particulièrement du fait de la position géographique et des types de logements, de la qualité de la construction de ces derniers, ou encore de l'exclusion sociale de ces populations. D'autre part, selon la théorie de la résilience sociale, le concept de panarchie souligne les potentiels effets des perturbations socio-économiques sur les niveaux d'inégalités, à travers par exemple la gestion de la relance post-catastrophe (Allen & al., 2014). Les phénomènes de cyclones tropicaux constituent une telle source de perturbation : selon les décisions économiques prises par les instances dirigeantes d'un pays, les inégalités peuvent s'accroître ou diminuer. Certaines études telles que Toya & Skidmore (2014) établissent un lien entre cohésion sociale et catastrophes naturelles. L'occurrence de catastrophes naturelles a des effets bénéfiques sur le niveau de confiance global au sein des populations. Dans le cadre de notre étude, cela pourrait se manifester par la mise en œuvre de davantage de mécanismes de solidarité et partage de risque au sein des populations, et *in fine*, à une diminution des inégalités de revenus.

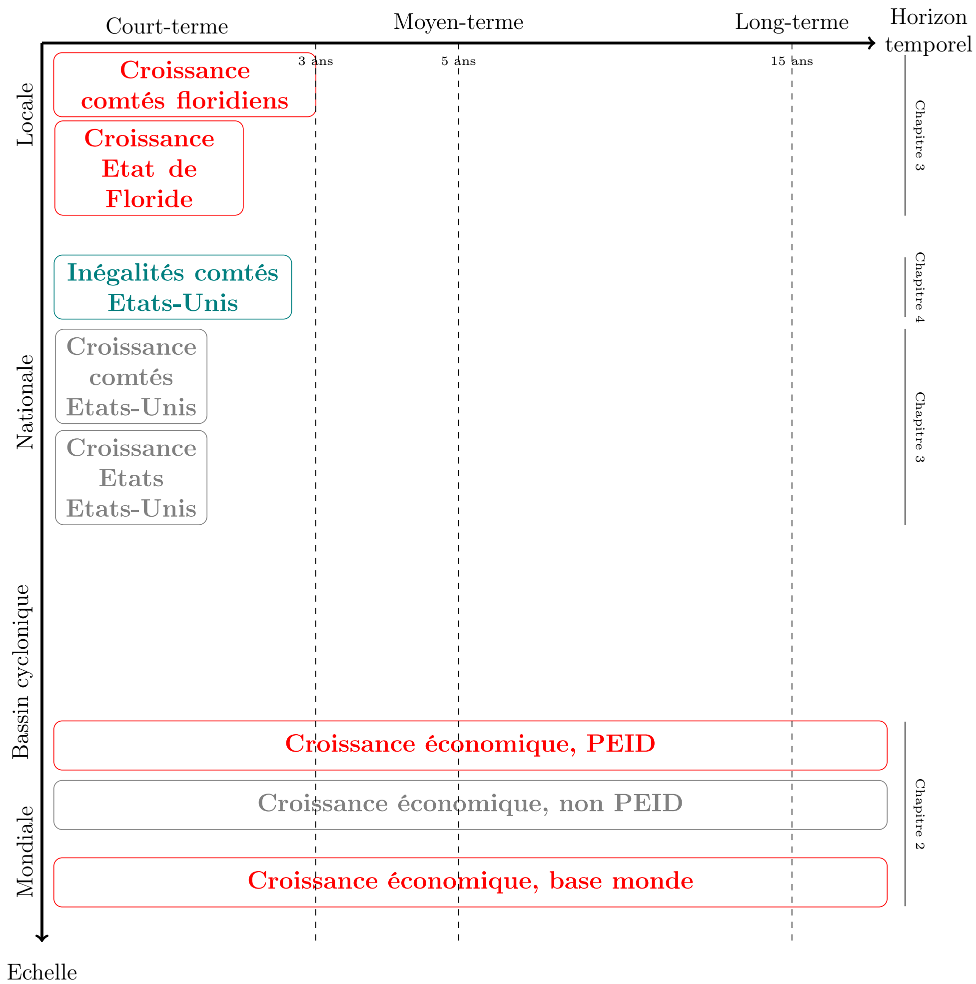
Plusieurs articles ont abordé cette question de recherche, à différentes échelles, et les conclusions révèlent dépendre grandement du pays étudié. Au Vietnam, en utilisant l'enquête sur les conditions de vie des ménages en 2008, Bui & al. (2016) trouvent que les catastrophes naturelles sont une source d'augmentation des inégalités de revenus. Abdullah & al. (2016), en étudiant le cas de la région du Sundarbans au Bangladesh, reportent des effets bénéfiques sur l'indice de Gini après le passage du cyclone Aila en 2009. Dans une étude longitudinale sur base monde, Yamamura (2015) décèle un accroissement des inégalités dû aux catastrophes naturelles sur un court-terme, *i.e.* 5 ans, mais rien au-delà de cet horizon temporel. Keerthiratne & Tol (2018) démontrent l'impact bénéfique des catastrophes naturelles sur les inégalités de revenus au Sri Lanka à l'aide de données d'enquête.

Etant donné que les cyclones représentent surtout une menace pour le capital matériel, certains pourront penser à juste titre que l'analyse des effets sur les inégalités de richesse serait plus pertinente. En ce sens, nous soutenons ici que l'accumulation de richesse dépend principalement des revenus perçus, et n'est pas seulement déterminé par stock d'actifs possédés à un instant t. L'estimation des effets sur les inégalités de revenus constitue donc une première étape vers celle des effets sur les inégalités de richesse.

Les résultats montrent une réduction du niveau des inégalités l'année où un comté est affecté. La part des revenus captée par les plus modestes (20 %, 40 % et 60 % les plus pauvres) augmente avec l'intensité cyclonique l'année où le pays est touché, lorsque celle du cinquième quintile diminue. Aucun effet n'est décelé sur les top 5 % les plus riches. Une analyse des effets de composition derrière ce résultat principal révèle plusieurs éléments. Tout d'abord, cet effet bénéfique est porté par les deux premiers quintiles de la distribution des revenus ainsi que le dernier. Ensuite, l'effet marginal cumulé reste de même amplitude deux ans après l'occurrence cyclonique, ce qui signifie que les mécanismes à l'origine de la diminution des inégalités de revenus sont maintenus pendant au moins deux années. Cette analyse de court-terme suggère aussi que l'occurrence d'un autre cyclone un an ou deux ans auparavant est bénéfique, car les effets contemporains sont renforcés par la prise en compte des expériences passées. De plus, nos résultats rejoignent les conclusions de Deryugina (2017) et de Pleninger (2022) car nous détectons une augmentation des dépenses d'assurance chômage en direction des populations les plus pauvres ainsi que des pertes de revenus du capital, imputables en grande partie aux populations les plus aisées.

Cette thèse aborde donc la problématique des conséquences macroéconomiques des cyclones tropicaux au travers d'un plan thématico-géographique. Les conséquences sur la croissance économique ou sur les inégalités de revenus sont étudiés. L'analyse de l'impact sur d'autres variables économiques telles que l'investissement, différentes sources de revenus ou encore l'emploi selon la situation financière apparaît, selon les chapitres, lorsque les mécanismes de transmission permettant d'expliquer les résultats principaux sont décryptés.

La structure générale de cette thèse ainsi que ses résultats peuvent être schématisés de la manière suivante :



Note : un élément tracé en rouge désigne un effet négatif, tandis qu'un élément bleu désigne un effet bénéfique, et un élément gris représente une absence d'effet.

Figure 1.4: Synthèse de la structure et des résultats de la thèse

Chapter 2

Tropical cyclones and economic growth: the importance of considering small island developing states

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Abstract

A number of empirical studies have explored the short and long-run economic relationship between tropical cyclones and national growth rates, but no general conclusion can be drawn from them so far. While negative effects are found in samples of exposed countries worldwide, cyclone shocks also show no significant influence in other national-level analyses. Using cross-country panel datasets for 83 affected nations between 1970 and 2015, this paper further investigates this issue by distinguishing a sub-group of nations which is particularly exposed to cyclonic risk and characterized by structural factors of economic vulnerability: small island developing states (SIDS). To capture tropical cyclones' overall impact on economic activity, a set of exogenous climatic indicators is built by combining physical intensity data with information on exposed areas. A negative and persistent impact is found for the sub-group of SIDS, while no effect is observed for other countries irrespective of their level of development. On impact, an additional km/h of intensity over a SIDS reduces *per capita* GDP growth by 0.016 percentage points, and this negative effect accumulates to -0.024 percentage points 15 years later. In contrast, more local approaches are suggested for non SIDS. The estimated negative impact on SIDS appears to be driven by an increased dependence on foreign economic conditions, insufficient reconstruction capacities and difficulties to implement adaptation policies.

Keywords: Natural disasters; Cyclones; Growth; Economic impacts; Environmental risk; Small Island Developing States
JEL classification: O44; Q54; Q56; R11

2.1 Introduction

Tropical cyclones are arguably one of the most damaging and threatening natural disasters for human systems. Among other examples, Cyclone Bhola, which struck East Pakistan (present-day Bangladesh) on 12-13 November 1970, remains known as the world's deadliest storm to ever devastate a coastal area, with an estimated death toll of 300,000 to 500,000 people. More recently, the 2005 Hurricane Katrina caused the displacement of approximately 650,000 people and destroyed more than 200,000 homes along the US Gulf Coast. In a context of intensified global climate change, with expected alterations in the frequency and intensity of storm events (Knutson & al., 2010; IPCC, 2019), these climate-related shocks may become a serious source of economic fluctuations in coming years, and it is of considerable importance to assess their impact on economic activity.

Several empirical studies have already addressed this question from short- to long-run, but conclusions vary depending on the scale chosen. While Felbermayr & Gröschl (2014) or Krichene & al. (2021) find evidence of negative and persistent effects of tropical cyclones on economic growth using universal datasets, Strobl (2011) or Zhou & Zhang (2021) show that these extreme events are not disruptive enough to be reflected in national economic growth rates in the U.S. or in Hong-Kong respectively.[1] Hence, this paper exploits key dimensions across which one might expect the economic impact of cyclone shocks to be heterogeneous. First, since cyclone events are primarily localized along coastal areas, they may only affect a reduced share of national economies. Even though massive losses can be generated locally, it is not obvious how cyclone events can shift aggregate output growth patterns. Apart from the geographic dimension, another aspect to consider is the level of development. In the more general framework of natural disasters, developing countries are almost always found to be more adversely affected than advanced economies (Kahn, 2005; Fomby & al., 2013). Developing countries tend to have agricultural-based economies and may thus experience stronger effects from weather shocks such as cyclone events. Cyclones can trigger a number of catastrophes like floods or landslides, potentially causing losses of crops that spread to the rest of the economy. Moreover, Noy (2009) demonstrates the better ability of developed countries and bigger economies to overcome disaster shocks than their developing or small counterparts.[2]

The combination of these two factors brings to light a sub-group of countries: Small Islands Developing States (SIDS). Due to the environmental and development challenges they face, the United Nations recognized SIDS as a specific case among worldwide countries in 1992. SIDS are today the focus of many political and scientific debates. These countries are characterized by a broad spectrum of structural factors of vulnerability regarding environmental risk, and their existence is even threatened by climate change's impacts such as sea level rise (IPCC, 2019). Storm events may threaten SIDS more due to their smallness,

[1] This issue is identical within the more general literature on natural disasters which provides a wide range of results as well. While Skidmore & Toya (2002) document positive effects of natural disasters on growth, Noy (2009) stresses mixed results, and Hochrainer (2009) concludes on overall negative effects worldwide.

[2] In particular, greater openness to international trade, higher *per capita* income, or governments' capacity to increase public spending are important determinants in attenuating natural disasters' adverse macroeconomic impacts.

insularity, limited domestic market and remoteness for some of them. SIDS' ability to thrive is often based on their shoreline regions which are exploited for tourism and marine-related activity (Briguglio, 1995). Since their total area is small relative to other countries, their scope for economic diversification is proportionally restricted. This renders SIDS highly dependent on international trade and vulnerable to economic fluctuations abroad. Risk exposure in SIDS is therefore more homogeneous compared to a larger country, and their entire economy is likely concerned when a storm strikes. As tropical cyclones can represent a national concern in SIDS, local governments arguably have a greater capacity to respond nationally in the aftermath of catastrophes. However, SIDS have, on average, higher levels of public debt than other developing countries, which restricts space for fiscal stimulus post-disaster (OECD, 2018). Méheux & al. (2007) detail all different types of impact of natural disasters on SIDS' biophysical and human systems. In addition, they point out the scarcity of SIDS-specific studies on the economic impact of natural disasters as well as a bias within the disaster literature towards studies on developed countries, as already highlighted in Khondker (2002). Most of articles on natural disasters' impact on SIDS turn out to be case-by-case investigations. For instance, Benson (1997) or Fairbairn (1997) focus on the 1993 cyclone Kina in Fiji. In the same way, McKenzie & al. (2005) focus on a selection of events in Fiji, Niue, Tuvalu and Vanuatu to stress their negative impact on local economies. Alternative sources of information are otherwise government and relief agencies' statistical reports which consist of a statement of facts without in-depth discussion on the impacts. Conscious of the need for better impact information based on general observations on SIDS economies, this paper contributes to filling this gap in the literature by studying overall patterns of impact in the wake of tropical cyclone events.

Using a worldwide database of 83 nations affected during the period 1970-2015, this paper aims to capture the overall effects of storm shocks on national economic growth in SIDS and non SIDS, respectively. To do this, geophysical and meteorological data sources are used to construct exogenous and accurate measurements of cyclone intensity, precipitation and temperature for each country during the sample period.[3] As stated above, it is relevant to control for local climatic parameters that can increase tropical cyclones' intensity or trigger various natural disasters. All these measurements are built in accordance with the definition of vulnerability in IPCC (2019), namely, physical intensity and degree of exposure at national scale are combined. The empirical framework follows Dell & al. (2012) and is based on earlier work by Bond & al. (2010). It consists of a distributed lag model. To preview the paper's results, the sub-group of SIDS is distinguished within the worldwide sample and results are analyzed using a similar strategy than in Krichene & al. (2021). Splitting the initial sample in such a way provides novel results. Consistent evidence for quasi-constant growth losses from short- to long-run is found for SIDS. On impact, an additional km/h of intensity over a SIDS decreases growth by 0.016 percentage points, and these growth losses accumulate to -0.024 percentage points after 15 years. However, as for non SIDS, when these countries are considered as a group, in no case are the results significant: cyclone events do not appear to be economically important enough to affect

[3] Using physical characteristics of weather events is opposed to economic-based indicators such as death toll, the total amount of damages etc., which are subject to reverse causality bias and other sources of endogeneity from exploitable data sources. See Felbermayr & Gröschl (2014) for a detailed discussion.

national economic growth rates irrespective of their level of development. Local approaches should be privileged for the latter sub-group of countries, focusing fundamentally on regions that are exposed and vulnerable to tropical cyclones.

To further explore the results obtained for SIDS, transmission mechanisms are analyzed with a focus on economic and physical channels. The existing empirical literature usually proceeds through the study of cyclones' impacts on economic or non-economic growth determinants, or estimates whether these determinants mitigate or amplify the observed output growth losses (Mohan & al., 2018; Krichene & al., 2021). Instead, this paper first investigates the effects on an outcome variable that is specifically designed to characterize SIDS' economic vulnerability: the degree of dependence to foreign economic conditions (Briguglio, 1995). Then, effects on *per capita* investment growth and construction sector GDP growth are examined to study SIDS' ability to recover and rebuild after the disaster. Lastly, growth effects of tropical cyclones are explored in more detail by distinguishing the most frequently exposed SIDS. This last analysis provides some insights on the adaptive capacities of SIDS. Results show that SIDS' dependence on foreign markets is amplified for five years after a cyclone strike, but also that their recovering capacities are dampened by the absence of effect on *per capita* investment or on construction sector GDP growth. Finally, growth losses are not attenuated for those most frequently exposed, which reveals a lack of adaptability to tropical cyclones. These transmission channel examinations suggest the existence of poverty traps at least in frequently exposed SIDS, as the latter are unable to rebuild entirely between each disaster event and constantly remain in a stage of reconstruction (Hallegate & Dumas, 2009).

This paper contributes to several strands of the literature. First, by distinguishing SIDS, it investigates a source of heterogeneity existing in worldwide samples when studying national growth responses to cyclone shocks. Findings shed light on the differentiated impact for those combining, among others, small country size as well as a lower level of development. Then, it contributes to debates on maximum lag choice to study cyclones' long-run effects. While other studies choose to employ 5 lags (Felbermayr & Gröschl, 2014), or 15 lags (Krichene & al., 2021), this paper rather demonstrates that this choice is not crucial since coefficients associated with lagged variables are rarely statistically significant. However, as for SIDS, cumulative growth losses are always negative and significant, meaning that the contemporaneous negative impact is not counteracted either in future response periods. Third, it contributes to the literature on SIDS, particularly their economic resilience when facing tropical cyclones. To date, this paper is the first one to estimate the causal effects of tropical cyclones with a focus on SIDS economies, even though their increased exposure and vulnerability to environmental risk relative to other countries is commonly admitted.

The remainder of the paper proceeds as follows. Section 2 describes the data sources used in the analysis. Section 3 details the construction of weather intensity measurements and presents the estimation strategy. Section 4 examines main findings and checks for their robustness. Transmission mechanisms are discussed in section 5, and section 6 concludes.

2.2 Data

2.2.1 Cyclone data

The raw data on cyclone events come from the Tropical Cyclone Exposure Database (TCE-DAT; Geiger & al., 2018), which provides consistent country-event-level data on cyclone intensity and exposure from 1950 to 2015. TCE-DAT filters 2713 landfalling tropical cyclones with at least 34 knots ($\approx$ 63 km/h) wind speed and sustained at least one minute from the widely used International Best Track Archive for Climate Stewardship (IBTrACS; Knapp & al., 2010). Since the IBTrACS data only identify geographic coordinates of each tropical cyclone's eye, the wind field model proposed by Holland (2008) is subsequently applied in order to get an overall cyclone trajectory and intensity at 0.1° latitude x 0.1° longitude grid cell level for each event recorded in the database. A cyclone is considered to be landfalling if at least one grid cell of a country is affected by the simulated wind field. It means that for a given country, all the storms affecting neighboring countries are considered as long as they pass by near enough to be felt. Figure 2.1 presents the average wind speed for all tropical cyclone events across years at the pixel level for all five tropical cyclone basins defined by the World Meteorological Organization (WMO): North Atlantic and North East Pacific, North West Pacific, South West Indian Ocean, Arabian Sea and Bay of Bengal, South West Pacific and South East Indian Ocean. Even though the formation of tropical cyclones can be identically described from a physical point of view across these different basins, each has its own characteristics and climatic conditions that affect the timing, intensity, and trajectory of tropical cyclones. For example, the North Atlantic basin's tropical cyclone season reaches its peak from June to November, while in the South West of the Indian Ocean, the season is from November to April.[4]

This figure supports IPCC (2019) as it shows that exposure to cyclonic risk is unequal between countries, especially small and large ones. It highlights the existence of fluctuations in annual mean cyclone wind speed within countries. In fact, tropical cyclones lose their strength as they get deeper in land, which is due to increasing surface roughness and friction. When making landfall, tropical cyclones are deprived of their main energy source which corresponds to water. Alternatively, this figure shows that tropical cyclones can cover large distances and affect countries located outside tropical cyclones' latitude lines. In such cases, tropical cyclones progressively transform into extratropical cyclones, sometimes called mid-latitude cyclones. The latter meteorological phenomena have different physical properties than tropical cyclones. However, they are still characterized by low-pressure centres and can also bring serious damages *via* storm surges, landslides, extreme winds, heavy rain etc. Since this paper aims to capture the overall effects of tropical cyclones, the sub-group of countries affected by extratropical cyclones that were initially tropical cyclones is also included in the sample. More specifically, the included extratropical cyclones are only those that are the consequence of a prior tropical cyclone formation. In addition to information on exposed land and local wind speed intensity, the dataset provides gridded estimates of the exposed population, which is used to study the robustness of main results presented in

[4]These basins are defined within the framework of WMO's Tropical Cyclone Programme (TCP). For further information, see `https://community.wmo.int/tropical-cyclone-regional-bodies`.

section 2.4.

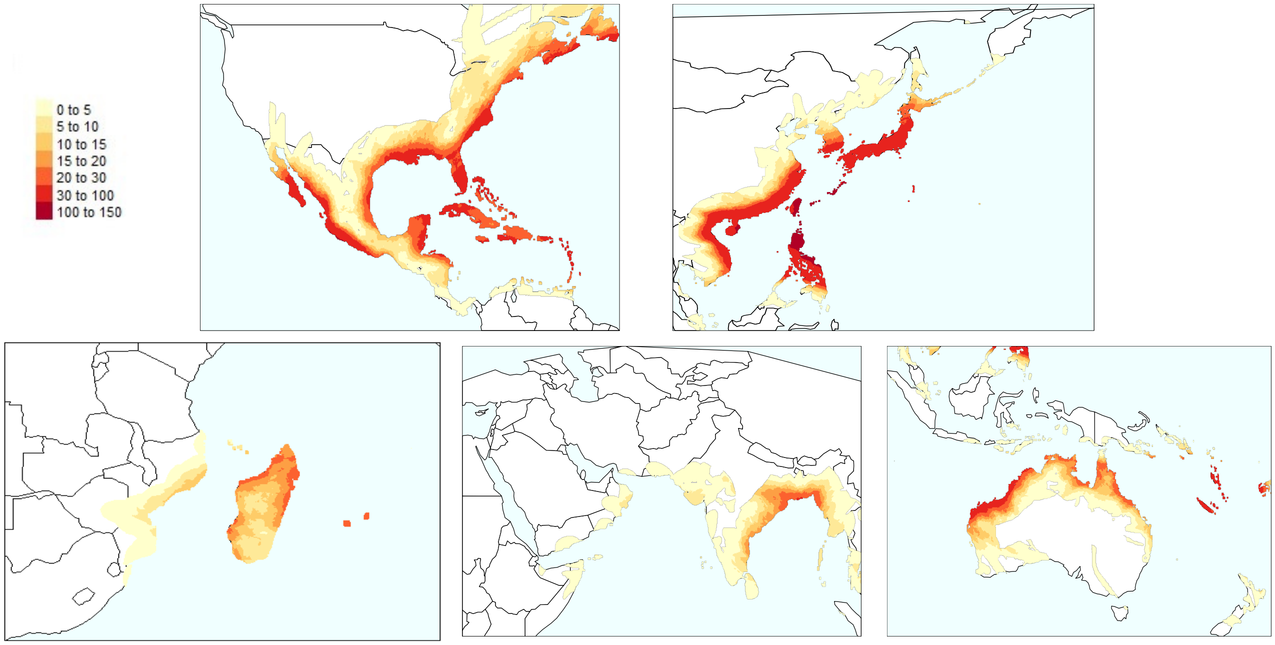

Figure 2.1: Annual average maximum wind speed (in km/h) from 1950 to 2015 at pixel level for all five tropical cyclone basins: North Atlantic and North East Pacific basin (upper section, left-hand side), North West Pacific basin (upper section, right-hand side), South West Indian Ocean basin (lower section, left-hand side), Arabian Sea and Bay of Bengal basin (lower section, middle), and South West Pacific Ocean and South East Indian Ocean basin (lower section, right-hand side).

The 83 nations included in the study have all faced at least one cyclone event during the sample period and are mainly distributed across tropical cyclone basins. 9.6 % of them are located in the South West Indian Ocean basin, 13.3 % in Arabian Sea and Bay of Bengal basin, 8.4 % in North West Pacific basin, 32.5 % in North Atlantic and North East Pacific basin, and 19.3 % in South West Pacific and South East Indian Ocean basin. Remaining nations (16.9 %) constitute a group affected mainly by extratropical cyclones.

2.2.2 Temperature and precipitation data

As cyclone events can trigger many hazards when making landfall, and their intensity can be linked with local atmospheric conditions, including additional climatic variables appears to be particularly relevant in this study. Temperature and precipitation correspond to such climatic controls. Both of these parameters are correlated with cyclone events, exogenously determined and can affect annual growth rates (Dell & al., 2012). Data on precipitation and temperature levels were obtained from the *Climatic Research Unit gridded Time Series* database (CRU TS; Harris & al., 2020), which provides monthly estimates derived from land-based weather station observations. Total monthly precipitation data are recorded in millimetres, and temperatures are measured in °Celsius. Both variables are collected at 0.5° latitude × 0.5° longitude resolution. As in TCE-DAT, the gridded data are then matched to each corresponding country-year level. Data are available from 1901 to 2019.

Detailed national summary statistics for sample nations are presented in Appendix Table A.2.1. China, Philippines and Japan are most affected by cyclone events, with more than three cyclones per year in the period 1950 - 2015. The most frequently hit SIDS are Bahamas, followed by Vanuatu and Cuba, with around one cyclone per year from 1950 to 2015. Moreover, a comparison of the annual wind speed relative to the exposed surface and the level of rainfall gives support for Haiyan & al. (2008) as they are positively related.

2.2.3 Economic data

Information on *per capita* GDP and other GDP components that are used in section 2.5 comes from the *United Nations Statistics Division* (UNSD, 2020). UNSD database provides data without gaps for the baseline panel of 83 countries from 1970 to 2015.[5] While the main results focus on *per capita* GDP growth, data on imports and exports of goods and services, GDP, gross capital formation and sectoral GDP for the construction industry are exploited for the analysis of transmission mechanisms. All values are recorded from National Accounts in constant 2015 prices in US Dollars and reported by international or national statistical services.[6]

2.3 Methodology

This section examines the empirical framework chosen for analyzing the impact of storm shocks on economic growth. The measurement of cyclone intensity at country-year level is entirely based on the physical characteristics of the disaster. It is designed to be in line with the definition of vulnerability suggested by the IPCC (2014). Vulnerability relates the intensity of a specific natural disaster with its effects on natural and human systems given the specific exposure. Cyclone intensity refers to the strength of the cyclone. As this weather system is characterized by rotating winds around a zone of low atmospheric pressure, several parameters can be used to describe a cyclone's intensity such as its central pressure, size, duration or even the storm surges it generates. All these parameters are often interrelated, and most of the intensity scales such as Saffir-Simpson Hurricane Wind Scale in the North Atlantic basin are based on wind speed levels. Here, information on wind speed intensities is combined with spatial aspects of the question. As argued by Skidmore & Toya (2002), the impact of a given natural disaster on the economy of a country depends on the disaster's intensity and is relative to the overall size of the country. Hence, cyclone events are measured as a spatially-weighted average of the maximum sustained wind speed over all pixels in a country. This normalization approach is also in line with Nordhaus (2006) as it aims to determine the average effect of storms on an average pixel for a given country. Finally, this measurement method is quite similar to the one established by Hsiang & Jina

[5] Except for the nations created after 1970 and included in the sample, *i.e.* Russia, Timor-Leste and Yemen.

[6] `https://unstats.un.org/unsd/snaama/Downloads`

(2014) and provides an estimate of a cyclone's average intensity in a randomly selected unit of land for each country. It can be expressed as follows for each country i and year t:

$$\overline{Cyc}_{i,t} = \frac{\sum_p \max_p \{Wind_{p,i,t}\} * Area_p}{LandSize_{i,t}}$$

$Wind_{p,i,t}$ are the local wind speed estimates in km/h for each pixel p, and $Area_p$ the exact area of pixel p in km^2 measured with respect to the corresponding latitude and longitude values, and $LandSize_{i,t}$ are total areas reported in the *World Development Indicators* (WDI) database of the World Bank.

In addition, one might notice that the pixel level wind speed is selected as the maximum wind speed value felt each year, as in Felbermayr & Gröschl (2014), irrespective of the number of cyclone events identified during this year.

Table 2.1 examines regional statistics for this indicator over equally split time intervals of the sample period. It shows that the North West Pacific and South West Pacific/South East Indian Ocean tropical cyclone basins have both a long-lasting greater exposure. Countries located outside tropical cyclone basins have the lowest values on average, which is explained by a lower frequency of events.

Table 2.1: Regional summary statistics for the cyclone intensity measurement $\overline{Cyc}_{i,t}$

	Average values		
Region/cyclone basin	1970-1985	1985-2000	2000-2015
Arabian Sea and Bay of Bengal	1.88	6.35	4.74
North Atlantic and North East Pacific	18.23	20.02	22.12
North West Pacific	35.36	43.46	29.54
South West Indian Ocean	8.28	12.43	11.46
South West Pacific and South East Indian Ocean	18.08	29.07	22.27
Other regions	2.49	2.53	2.92

As the effects of cyclone events on economic activity depend on local climatic conditions, annual measurements for temperature and precipitation are also constructed. These measurements bring relevant climatic control variables linked with storms as pointed out by Dell & al. (2014). The average annual temperature ($\overline{Temp}_{i,t}$) is measured in °Celsius and is calculated by averaging monthly temperature records for each country while the annual precipitation level ($Prec_{i,t}$) is obtained by summing monthly precipitation levels during a given year and is recorded in millimeters. Table 2.2 examines the fluctuations between countries for these three input variables as well as the frequency of cyclones and our variable of interest, *i.e.* economic growth ($g_{i,t}$) during the sample period. It also provides detailed statistics for SIDS and non SIDS, respectively. The maximum average value for the cyclone intensity measurement is reached by Philippines (105.3 km/h), while Tanzania has the lowest (0.002 km/h). The latter country has only one cyclonic year identified in the database. Vanuatu is the SIDS having the highest average cyclone intensity value with 74.1 km/h during the period 1970-2015. It is also the most frequently hit SIDS during the sample period, with an average of 1.6 cyclone events per year from 1970 to 2015 ($Nb\, Cyc_{i,.}$), while China is the most frequently hit country worldwide, with more than 8 cyclones per year during the sample period. Hence, on average, SIDS are more intensely affected than non SIDS, but not in absolute value. The latter point is further explored in Figure 2.2, which shows the fat-tailed distribution of cyclone intensity for non SIDS, compared to a more homogeneous exposure in SIDS. The hottest country in the sample is Somalia, with an average temperature of 27.3°C over the sample period, and the coldest is Canada, with an average temperature of -4.9°C. Finally, the highest average annual rainfall level from 1970 to 2015 is recorded for Dominica, with 3602.1mm per year. The driest nation is Saudi Arabia with an average rainfall level of 75.1mm. This table further stresses that SIDS face higher average storm intensities than other countries. Additionally, Table 2.3 presents Pearson correlation coefficients for input variables and population density. Among others, it displays a positive and statistically significant correlation between the cyclone indicator and the frequency of cyclones or with population density (see also Appendix A - Figure A.2.1). Particular attention is brought to the latter point in the robustness checks section of the paper. This table also shows a positive correlation between precipitations or temperature and the cyclone measurement, which confirms that these two variables are pertinent control variables.

Table 2.2: Descriptive statistics

Variable	Variable Description	Min.	Max.	Median	Mean	Std Dev.
$\overline{Cyc}_{i,.}$	Cyclone intensity measurement	0.002	105.3	5.8	16.0	21.1
SIDS		*1.6*	*74.1*	*29.1*	*28.1*	*16.5*
Non SIDS		*0.002*	*105.3*	*2.4*	*9.6*	*20.5*
$Nb\ Cyc_{i,.}$	Annual number of cyclones	0.02	8.4	0.4	0.9	1.7
SIDS		*0.02*	*1.6*	*0.4*	*0.5*	*0.4*
Non SIDS		*0.02*	*8.4*	*0.2*	*1.1*	*2.0*
$\overline{Temp}_{i,.}$	Temperature	-4.9	27.3	24.7	21.5	7.4
SIDS		*22.4*	*27.2*	*25.5*	*25.4*	*1.3*
Non SIDS		*-4.9*	*27.3*	*23.0*	*19.4*	*8.4*
$Prec_{i,.}$	Level of precipitation	75.1	3602.1	1613.3	1605.4	862.5
SIDS		*364.3*	*3602.1*	*2090.1*	*2059.1*	*693.5*
Non SIDS		*75.1*	*2935.2*	*1208.1*	*1361.8*	*850.8*
$g_{i,.}$	*Per capita* GDP growth	-0.02	0.08	0.02	0.02	0.02
SIDS		*-0.01*	*0.05*	*0.02*	*0.02*	*0.01*
Non SIDS		*-0.02*	*0.08*	*0.02*	*0.02*	*0.02*

Notes: Average values within countries from 1970 to 2015. Cyclone intensity measurement is in km/h, temperature in degrees Celsius, and precipitation in millimeters. 83 countries (29 SIDS and 54 non SIDS).

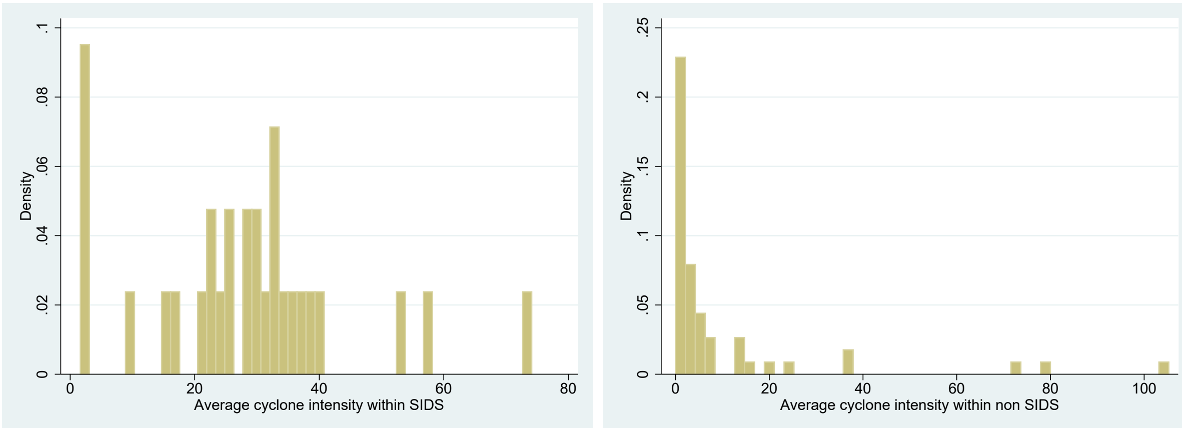

Figure 2.2: Distribution of average values within countries from 1970 to 2015 of the cyclone intensity measurement for small island developing states (left-hand side), and the world sample excluding small island developing states (right-hand side).

Notes: Estimations with outlier-robust regression. Standard errors are computed using the Street & al. (1988) correction. Shaded areas represent the associated 90 % confidence intervals.

Table 2.3: Pearson correlation matrix

	$\overline{Cyc}_{i,t}$	$Nb.\ Cyc_{i,t}$	$\overline{Temp}_{i,t}$	$Prec_{i,t}$	$Population\ Density_{i,t}$
$\overline{Cyc}_{i,t}$	1.00				
$Nb.\ Cyc_{i,t}$	0.42***	1.00			
$\overline{Temp}_{i,t}$	0.12***	-0.13***	1.00		
$Prec_{i,t}$	0.23***	-0.041**	0.41**	1.00	
$Population\ Density_{i,t}$	0.14***	0.0091	0.093***	0.17***	1.00

Notes: Pairwise correlation coefficients. Significance levels : *** 1 % ; ** 5 % ; * 10 %.

From the immediate to the long-term perspective, the dynamic adjustment path of the exogenous and scale-invariant predictor of cyclone events on *per capita* GDP growth rate is analyzed controlling for country-level climatic conditions and usual country and year fixed effects (μ_i and η_t, respectively). In the spirit of Dell & al. (2014), and to a lesser degree Krichene & al. (2021), no economic control variables are included so that correlations with the dependent variable and further over-controlling issues are avoided. The latter point stems from the definition of "bad controls" by Angrist & Pischke (2014): the inclusion of any macroeconomic determinants of growth as a control variable does not remove omitted variable bias, but instead, captures a part of the causal effect. Determinants of growth can therefore equally be included as dependent variables. We also choose to employ a static specification to align with the most recent empirical literature on our topic (Hsiang & Jina, 2014; Kunze, 2021; Krichene & al., 2021). The equation of interest is based on the model developed in Dell & al. (2012) in the context of weather shocks. More specifically, it takes the form of a distributed lag model, and it is given by:

$$g_{i,t} = \alpha + \sum_{j=0}^{L} \beta_j \overline{Cyc}_{i,t-j} + \sum_{j=0}^{L} \gamma_j \overline{Temp}_{i,t-j} + \sum_{j=0}^{L} \delta_j Prec_{i,t-j} + \mu_i + \eta_t + \varepsilon_{i,t} \tag{2.1}$$

Where $\varepsilon_{i,t}$ denotes the white noise error term and $g_{i,t} \equiv \dfrac{y_{i,t} - y_{i,t-1}}{y_{i,t-1}}$, with $y_{i,t}$ *per capita* GDP.

Following the approach of Noy (2009), one crucial feature of the model is the inclusion of a temporal weight for $j = 0$ to the cyclone measurement so that the immediate impact is captured more accurately. It seems reasonable to assume that the earlier the cyclone occurs in a given year, the bigger its impact on the same year. This choice is crucial as the immediate impact is likely to drive future periods' responses. For $j = 0$, the cyclone indicator can therefore be rewritten:

$$\overline{Cyc}_{i,t} = \frac{\sum_{p} \max_{p}\{Wind_{p,i,t}\} \times Area_p \times \dfrac{(12 - m_p)}{12}}{LandSize_{i,t}}$$

With m_p the month in which the cyclone occurred in pixel p.

This paper ultimately analyses the marginal cumulative effect of cyclone events. For a given lag horizon L, it is defined by:

$$\Omega_l = \sum_{j=0}^{l} \beta_j, l \in [\![0; L]\!] \tag{2.2}$$

In order to increase comparability with the existing literature, the baseline lag structure chosen in the marginal cumulative effect analysis follows Krichene & al. (2021) and is fixed at 15 years. As argued by Greene (2003), it is better to include too many than too few lags, since irrelevant extra lags would just be estimated as noise. Adding lags is also a way to control for past experiences of tropical cyclones. Still in line with this distributed-lag literature, in what follows, the immediate effect of tropical cyclones (*i.e.* the year that they occur, β_0) and the cumulative effect (Ω_L, with lag horizon $L > 0$) are separately estimated. As pointed out by Dell & al. (2012), the summation of cyclone coefficients corresponds to the growth effect of the weather shock. This distinction between immediate effect and cumulative growth effect raises questions about our results' implications in terms of short-term output gap and long-term potential growth. Nevertheless, as these concepts require additional data on employment or inflation, but also time-series smoothing techniques such as Hodrick-Prescott filter to remove cyclical components of growth (Giorno & al., 1995; St-Amant & van Norden, 1997), investigating them appears to be beyond the scope of this chapter which evaluates to what extent actual growth is affected by cyclone shocks.

Before running any estimation, one should also be cautious about panel unit root issues, especially for our dependent variable which is economic growth. To this end, we perform Levin-Lin-Chu and Im-Pesaran-Shin tests on balanced samples, *i.e.* excluding Russia, Timor-Leste and Yemen here. Both of these tests reject the presence of non-stationary panels at the 1 % level.

The baseline specification in equation (2.1) and the associated immediate and marginal cumulative effects can be estimated using the standard ordinary least squares (OLS) procedure. However, a deeper exploration of the data reveals the presence of outliers that influence the OLS estimator. In the present context, only growth rates outliers must be considered, as the latter can be driven by external economic shocks unrelated with natural disasters. In fact, extreme values of the climatic variables are determined by the nature, *i.e.* purely exogenous. Hence, overall impact of cyclone events must be captured given other socioeconomic shocks occurring the same year. In this study, many points are likely to be affected in such a way. Among others, high growth rates observed for Ireland in 2015 or Zimbabwe in 2009 are mainly due to changes in fiscal policies, while some negative growth rate points like Timor-Leste in 1999 or Yemen in 2015 are linked with political conflicts. These examples of influential observations are a source of serious concern as they can distort estimates obtained from OLS by providing excessive importance to extreme residual values. To cope with this issue, Li's (1985) robust regression is used. It downweights influential observations based on residual values.[7] This robust estimation technique has been used in a variety of topics such as financial economics (Kaplan & Zingales, 1997), political economy (Acemoglu & al., 2019), labor economics (Acemoglu & Restrepo, 2020) or international trade (Amiti & Wei, 2009), but the importance of using outlier-robust regression in the context of estimating causal effects of storm events on economic growth has been firstly underlined by Krichene & al. (2021). In the more general framework of natural disasters, Cavallo & al. (2013) conclude that no significant effect is found on economic growth once substantial socioeconomic disruptions following natural disasters are controlled for.[8]

2.4 Empirical results

The effect of cyclone events on economic growth is first measured for the entire set of cyclone-prone countries using a robust estimation technique based on equation (2.1). This replication of the empirical literature is shown in Appendix C. More importantly, this section presents separate analyses for SIDS and non SIDS, which are conducted by adding an interaction term with a dummy variable to the main model. This revised model corresponds to:

$$g_{i,t} = \alpha + \sum_{j=0}^{L} \beta_{j,1} \overline{Cyc}_{i,t-j} + \sum_{j=0}^{L} \beta_{j,2} \left(\overline{Cyc}_{i,t-j} \times SIDS \right) + \sum_{j=0}^{L} \gamma_j \overline{Temp}_{i,t-j} + \sum_{j=0}^{L} \delta_j Prec_{i,t-j} + \mu_i + \eta_t + \varepsilon_{i,t} \tag{2.3}$$

Across all estimations, standard errors are computed using the pseudovalues approach designed for robust regressions as in Street & al. (1988).

[7]See Appendix B for further details and statistics on influential observations and outlier-robust regressions.

[8]In particular, they refer to the Islamic Iranian Revolution of 1979 occurring at the dawn of the 1978 earthquake and the Sandinista Nicaraguan Revolution of 1979 following the earthquake of 1972.

2.4.1 Measuring the impact of cyclone events on economic growth: distinguishing small island developing states

Historically, special challenges faced by island developing countries have been raised and discussed at the United Nations since 1972, but the group of SIDS was recognized and founded later at the 1992 United Nations Conference on Environment and Development held in Rio de Janeiro, Brazil.[9] SIDS are located in the Caribbean Sea and the Atlantic, Indian and Pacific Oceans and are inherently characterized by a vast amount of social, economic and environmental issues. SIDS are particularly exposed to natural disasters and to further climate change impacts such as sea level rise. Here, the focus is on SIDS' economic vulnerability in the wake of cyclone events. The above descriptive statistics suggest that SIDS face higher average cyclone intensities than non SIDS (Table 2.2).

Distinguishing SIDS from the rest of the worldwide sample seems to be of great interest for geographical, economic, or political reasons. First of all, tropical cyclones may constitute a bigger threat to SIDS due to their smallness, insularity, limited domestic market and remoteness for some of them. A cyclone event can devastate coastal zones, which are intensely exploited for tourism and marine-related activity (Briguglio, 1995). Then, the smallness of their exploitable area poses a natural obstacle to economic diversification, weakening reconstruction capacities after a cyclone strike. As domestic production is often limited to a narrow range of goods, SIDS are strongly dependent on international trade and are sensitive to economic fluctuations abroad. In the end, this leads to higher per unit costs of production dedicated to rebuilding work, and this over-dependence on foreign exchanges is emphasized by extended supply schedules due to their frequent exclusion from major maritime and air routes. Besides, SIDS often rely on larger states in their political decisions and some aspects of public administration, which can undermine the efficiency in investment strategies or restructuring issues. All in all, the main sample is composed of 29 SIDS: 55% of them are located in the North Atlantic and North East Pacific tropical cyclone basin, 31% in the South West Pacific and South East Indian Ocean basin, 7% in the South West Indian Ocean basin, and the 7% remaining are located outside tropical cyclone basins.

Hence, even though SIDS are proportionally more exposed to tropical cyclones than non SIDS, it does not mean that the probability of being a SIDS is correlated to cyclone intensity. In fact, SIDS are defined by the United Nations as a group of countries that share common development challenges, and vulnerability to natural disasters is one of them. While most SIDS are located in regions that are prone to tropical cyclones, such as the Caribbean and the Pacific, not all of them experience this type of natural disaster. For example, some SIDS in the Indian Ocean, such as Maldives and Seychelles, are unexposed to tropical cyclones but are exposed to other climate-related hazards, namely sea level rise and ocean acidification, as many other SIDS. Exposure to tropical cyclones is, therefore, not a defining characteristic of SIDS but rather one of the challenges these countries face in order to achieve sustainable development.

Table 2.4 reports the results from estimating equation (2.3) without lag, with one lag, five lags, ten lags or fifteen lags for SIDS and non SIDS.[10] Estimates for each corresponding

[9] `https://www.un.org/ohrlls/content/about-small-island-developing-states`

[10] When $L = 15$, on average, each country is observed 31 years and 62 observations out of 2556 are

marginal cumulative effect are also shown on the table's bottom row. Figure 2.3 plots the time path of cumulative effect on *per capita* GDP growth from a cyclone strike at time 0 together with its corresponding 90 % confidence intervals for $L = 15$. The line $y = 0$ represents the counterfactual trajectory of the economy if the cyclone event had not occurred. Altogether, SIDS and non SIDS form a partition of the set of sample nations. Splitting the sample in such a way reveals the existence of a differential impact, and hence, that national growth responses obtained with the worldwide base mask some heterogeneity. The estimated immediate effect of one additional km/h of cyclone intensity over a SIDS is to decrease local growth rates by 0.016 percentage points. Then, focusing on the case when $L = 15$, this negative effect accumulates to -0.024 percentage points after 15 years (significant at the 5% level).[11] Put another way, a one standard deviation increase in cyclone intensity ($\sigma_{\overline{Cyc}_{i,t}} = 35.1$) is responsible for a growth penalty of 0.84 percentage points 15 years later. Across all other lag horizon choices, the null hypothesis that cyclones have no immediate effect on growth is rejected at the 1% level. Cumulative effects in SIDS are almost of same magnitude from short-run to long-run. Such a quasi-constant slope is explained by the fact that most of the lagged values cannot be distinguished from 0. More specifically, it indicates that SIDS manage to avoid an intensification of negative effects but do not manage to counteract them either. The null hypothesis that cyclone events do not affect in SIDS' growth rates in the year that they occur is rejected at the 1% level across all lag choices. In contrast, when non SIDS are considered as a group, point estimates tend to show they experience an increased growth in the short-run, which plummets in the long-run, but these results are not statistically significant and no conclusion can be drawn from them. Last but not least, our results partially confirm those of Dell & al. (2012). We find a negative contemporaneous effect of temperature on economic growth at a global scale, which statistical significance vanishes as we increase the number of lags. We also find a negative - though mostly insignificant - effect of precipitation on growth. The effect of temperature and precipitation on growth surely deserves more investigation in another work as the effect might differ across sectors or given the level of development.

One can argue that these negative effects observed for SIDS are driven by their development level. It is well-established in the literature on natural disasters and economic growth that poorer nations tend to experience stronger effects than richer ones (Rasmussen, 2004; Toya & Skidmore, 2007; Noy, 2009; Fomby & al., 2013). As such, Appendix D provides complementary estimations for the subset of developed countries, non SIDS developing countries and non SIDS developing countries which are highly dependent on the agricultural sector.[12] Marginal cumulative effects coefficients are always positive for both subgroups of developing countries, whereas the effects are positive in the short-run, then become nega-

dropped with the robust estimation technique. Different parameter calibrations which downweight observations less drastically are also tested in Appendix C - Figure C.2.2 and Figure C.2.3 and produce similar results.

[11]Detailed marginal effects coefficients for all estimations in subsection 4.1 are presented in Appendix C - Table C.2.2

[12]Developed countries are defined as in the *World Economic Outlook 2000* database of the International Monetary Fund. These countries are Australia, Canada, Hong Kong, France, Iceland, Ireland, Japan, New Zealand, Norway, Portugal, the Republic of Korea, Singapore, Spain, the United Kingdom, United States. High dependence on the agricultural sector is defined as having an above median share of agricultural production among total production. This threshold corresponds to 14%.

tive for developed countries. However, coefficients remain insignificant for either of those sub-groups of non SIDS countries, except in the very long-run for developed countries, after period 10.

Table 2.4: Regression results, models distinguishing small island developing states.

	No lag	1 lag	5 lags	10 lags	15 lags
	(1)	(2)	(3)	(4)	(5)
$\overline{Cyc}_{i,t}$	0.00012	0.00010	0.00010	0.00005	0.00006
	(0.00011)	(0.00011)	(0.00011)	(0.000012)	(0.00013)
$\overline{Cyc}_{i,t-1}$		0.00007	0.00005	0.00005	0.00004
		(0.00004)	(0.00004)	(0.00005)	(0.00004)
$\overline{Cyc}_{i,t-2}$			-0.00001	-0.00003	-0.00005
			(0.00004)	(0.00005)	(0.00005)
$\overline{Cyc}_{i,t-3}$			0.00003	-7.26e-06	-0.00003
			(0.00004)	(0.00005)	(0.00005)
$\overline{Cyc}_{i,t} \times SIDS$	-0.00028**	-0.00027**	-0.00025**	-0.00022*	-0.00021
	(0.00012)	(0.00011)	(0.00012)	(0.00013)	(0.00013)
$\overline{Cyc}_{i,t-1} \times SIDS$		-0.00004	-0.00003	-0.00002	-0.00003
		(0.00004)	(0.00005)	(0.00005)	(0.00005)
$\overline{Cyc}_{i,t-2} \times SIDS$			3.57e-06	-0.00002	0.00004
			(0.00005)	(0.00005)	(0.00005)
$\overline{Cyc}_{i,t-3} \times SIDS$			-0.00005	-0.00002	-5.46e-07
			(0.00005)	(0.00005)	(0.00005)
$\overline{Temp}_{i,t}$	-0.00384**	-0.00343*	-0.00281	-0.00111	-0.00197
	(0.00188)	(0.00194)	(0.00204)	(0.000211)	(0.00223)
$\overline{Temp}_{i,t-1}$		-0.00144	-0.00052	-0.00004	0.00363
		(0.00195)	(0.00209)	(0.00214)	(0.00229)
$\overline{Temp}_{i,t-2}$			-0.00290	-0.00294	-0.00255
			(0.00210)	(0.00215)	(0.00225)
$\overline{Temp}_{i,t-3}$			-0.00173	-0.00260	-0.00208
			(0.00206)	(0.00216)	(0.00223)
$Prec_{i,t}$	-2.50e-06	-1.30e-06	-9.98e-07	-1.92e-07	1.83e-06
	(2.33e-06)	(2.37e-06)	(2.49e-06)	(2.62e-06)	(2.74e-06)
$Prec_{i,t-1}$		-6.71e-06	-5.65e-06**	-4.66e-06*	-2.79e-06
		(2.38e-06)	(2.54e-06)	(2.65e-06)	(2.79e-06)
$Prec_{i,t-2}$			-3.71e-06	-1.61e-06	-2.56e-06
			(2.49e-06)	(2.61e-06)	(2.74e-06)
$Prec_{i,t-3}$			-6.46e-06***	-6.19e-06	-3.47e-06
			(2.47e-06)	(2.61e-06)	(2.71e-06)
Observations	3676	3676	3356	2956	2556
Adjusted R^2	0.25	0.25	0.27	0.29	0.32
Marginal cumulative effect (Ω_L) in SIDS	-0.00016***	-0.00014***	-0.00018***	-0.00022***	-0.00024**
	(0.00004)	(0.00005)	(0.00006)	(0.00008)	(0.00011)
Marginal cumulative effect (Ω_L) in non SIDS	0.00012	0.00017	0.00019	-0.00003	-0.00029
	(0.00011)	(0.00011)	(0.00015)	(0.00018)	(0.00022)

Notes: Outlier-robust regression estimates. Standard errors incorporating the Street & al. (1988) correction are in parentheses. Time and country fixed effects, as well as temperature and precipitation controls are included in all specifications, but not reported in the table.
Significance levels : *** 1 % ; ** 5 % ; * 10 %.

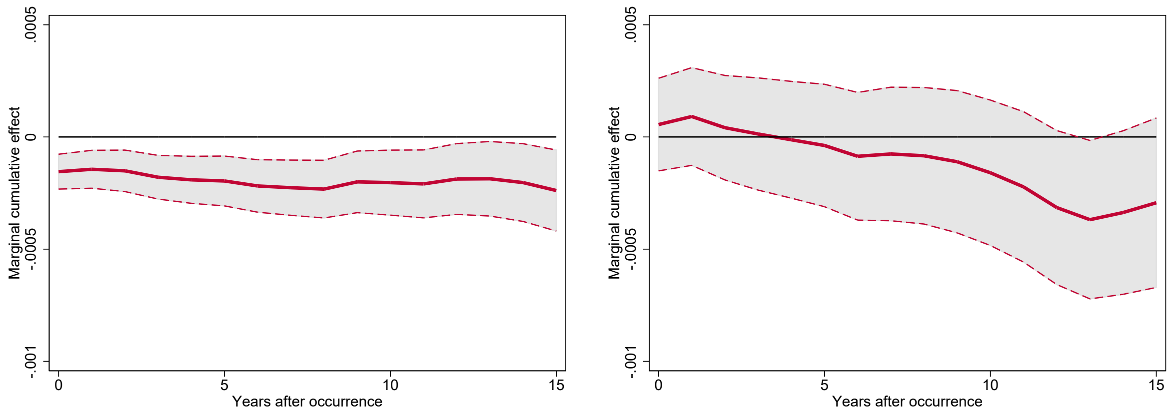

Figure 2.3: Measures of the marginal cumulative effects over fifteen years of cyclone events on *per capita* GDP growth for small island developing states (left-hand side), and the world sample excluding small island developing states (right-hand side).

Notes: Estimations with outlier-robust regression. Standard errors are computed using the Street & al. (1988) correction. Shaded areas represent the associated 90 % confidence intervals.

To make things clearer about the adverse impact observed on SIDS, Figure 2.4 displays a numerical simulation of an average *per capita* GDP trajectory during 15 years for a SIDS that would experience an increase in cyclone intensity of one standard deviation in year 0 as well as its trajectory if no cyclone occurred. In the latter case, growth rates for this "average SIDS" were simulated using a normal distribution with mean and standard deviation values defined in accordance with the descriptive statistics reported in Table 2.2 for this subgroup of countries (respectively 2% and 1%). Values exhibited for the scenario when a cyclone strikes are obtained using the coefficients associated with the cyclone intensity measurement and depicted in Table 2.4. The starting value for *per capita* GDP (7808.4 \$U.S.) corresponds to the average value observed for our sample of SIDS countries from 1970 to 2015.

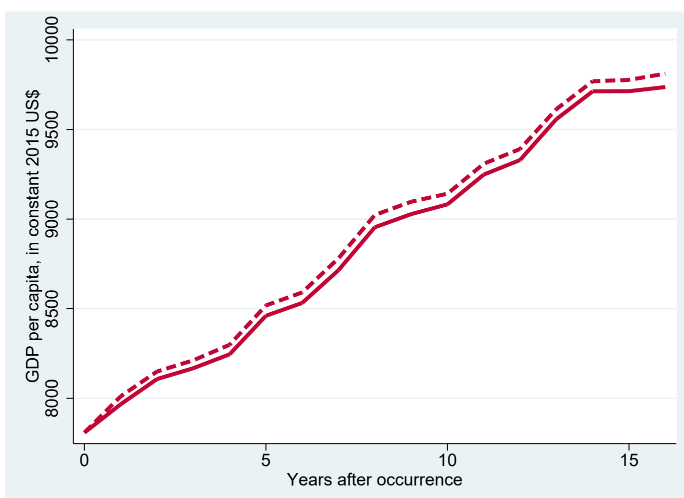

Figure 2.4: Simulation of an average *per capita* GDP growth dynamics for small island developing states under a scenario of a one standard deviation increase in tropical cyclone measurement occurring in year 0 (solid line), along with a scenario of no catastrophe (dashed line).

2.4.2 Robustness checks

This subsection presents a variety of robustness checks and proceeds in three steps. First, robustness to alternative cyclone measurements is considered following the existing literature. Then, main results' sensitivity to changes in weights is examined. And finally, alternative panel specifications are investigated.

Alternative cyclone measurements

Baseline estimations rely on a measurement of cyclones that combines intensity and share of exposed land. Intensity is measured as the maximum wind speed observed at the pixel level, and this point is questioned in several ways. In the context of Atlantic hurricanes landfalling along the U.S. Gulf and East Coasts, Emanuel (2011) introduced a threshold value for wind speed below which no property damage is likely to occur. This threshold value is equal to 50 knots ($\approx$ 92.6 km/h), and is calculated from insurance data in the US. It is embedded in the previously built cyclone measurement by only keeping cyclone events during which at least one pixel is hit by winds strictly greater than 92 km/h. Additionally, in the spirit of Krichene & al. (2021), a second index based on the exposed land and omitting the wind speed intensity dimension is examined. The latter measurement corresponds to a cyclone occurrence index relative to the exposed surface. Finally, the robustness of main estimations is checked when using the yearly number of cyclones rather than their intensity.

Table 2.5 reports the results from regressing these alternative cyclone measurements on *per capita* GDP growth using equation (2.3) and the outlier-robust estimator. Results are broadly consistent with previous findings as restricting to "damaging cyclones" only or omitting the wind speed parameter both exhibit larger effects. These larger point estimates are explained by a higher mean value for all identified cyclone events with the former indicator, and an equal consideration between cyclones of low and high wind speed intensity with the latter index. The persistent negative effect of cyclone events on economic growth in SIDS is also confirmed. Still, the cumulative effect is now statistically insignificant in final periods with the cyclone occurrence index when $L = 15$.[13] As for non SIDS, there is still no tangible evidence of any immediate or cumulative impact on national growth rates. Results when using the annual number of cyclones rather than cyclone intensity do not change the conclusions either, and the positive relationship observed between both variables is confirmed in SIDS. However, it is worthy to note that, despite the absence of statistical significance, results for non SIDS are consistently negative when studying the frequency of cyclones.

[13] Detailed results are available upon request.

Table 2.5: Regression results using alternative cyclone measurements

	SIDS (1)	Non SIDS (2)
$\overline{Cyc}_{i,t} \times \mathbb{1}_{\{\exists\ pixel\ p\ \mid\ Wind_{p,i,t} > 92km/h\}}$		
Immediate effect, $L = 0$	-0.00019***	0.00006
	(0.00004)	(0.00011)
Marginal cum. effect, $L = 1$	-0.00017***	0.00011
	(0.00005)	(0.00011)
Marginal cum. effect, $L = 5$	-0.00021***	0.00009
	(0.00006)	(0.00014)
Marginal cum. effect, $L = 10$	-0.00031***	-0.00009
	(0.00008)	(0.00018)
Marginal cum. effect, $L = 15$	-0.00036***	-0.00034
	(0.00011)	(0.00023)
$Wind_{p,i,t} = \mathbb{1}_{\{Wind_{p,i,t} > 0\}}$		
Immediate effect, $L = 0$	-0.01453***	0.01642
	(0.00457)	(0.01199)
Marginal cum. effect, $L = 1$	-0.01295***	0.02134*
	(0.00500)	(0.01273)
Marginal cum. effect, $L = 5$	-0.01768***	0.03292**
	(0.00688)	(0.01618)
Marginal cum. effect, $L = 10$	-0.01853**	0.01015
	(0.00957)	(0.02071)
Marginal cum. effect, $L = 15$	-0.01164	-0.02525
	(0.01263)	(0.02575)
$Nb.\ Cyc_{i,t}$		
Immediate effect, $L = 0$	-0.00423***	-0.00008
	(0.00126)	(0.00062)
Marginal cum. effect, $L = 1$	-0.00212	-0.00007
	(0.00171)	(0.00083)
Marginal cum. effect, $L = 5$	-0.00378	-0.00062
	(0.00282)	(0.00134)
Marginal cum. effect, $L = 10$	-0.00698*	-0.00185
	(0.00399)	(0.00182)
Marginal cum. effect, $L = 15$	-0.01270**	-0.00328
	(0.00580)	(0.00238)

Notes: Estimations with outlier-robust regression. Standard errors incorporating the Street & al. (1988) correction are in parentheses. Time and country fixed effects as well as temperature and precipitation controls are included in all specifications, but not reported in the table.
Significance levels : *** 1 % ; ** 5 % ; * 10 %.

Alternative weights

Table 2.6 reconsiders the main specification by applying alternative weights to the cyclone measurement. Firstly, as discussed in section 2.3, cyclone intensity is correlated with population density. Hence, instead of scaling the indicator by the share of exposed land, another strand of the TCE-DAT is exploited, *i.e.,* population weights. TCE-DAT provides spatially explicit population data for each cyclone event recorded in the database at $0.1° \times 0.1°$ resolution based on the *History Database of the Global Environment* v3.2 (HYDE; Klein Goldewijk & al., 2017).[14] The use of such weight constitutes a strong complement to the above results for two plausible reasons: it might be the case that a cyclone affects a wide area but sparsely populated, meaning that it does not affect an economically dynamic area. Analogously, a sparsely populated area could also be endowed with a high level of physical capital or natural resources (*e.g.* industrial or agricultural areas). In both cases, the intensity of the cyclone event and its trajectory within a given country remain unrelated to the intensity of economic activity at pixel level. In a second phase, the assumption that the immediate impact depends on the month in which the cyclone occurs is relaxed as it may be driving future responses and the successive adjustment path. As a final step, an extension of this monthly weight up to 3 years after the cyclone strike is also analyzed. In fact, the main specification assumes that a cyclone event occurring in January and another one occurring in December with the same trajectory and intensity are given an equal weight after period 0, which can seem simplistic since, in the former case, reconstruction processes and resilience can be more advanced than in the latter case.

Examining alternative weights continues to show substantial negative effects in SIDS. Results appear slightly larger in magnitude when using population weights, slightly lower when removing the period 0 temporal weight, and remain of same magnitude with an extension of the latter weight until lag 3. Concerning non SIDS, using population-weights or removing temporal weight now shows a significant negative cumulative effect in the very long-run. However, the latter results should be interpreted with caution since statistically significant values are highly sensitive to specification and only occur in final periods.

[14]HYDE provides decennial values up to 2000 and annual values afterwards. Thus, annual population data before 2000 are recovered with linear interpolation.

Table 2.6: Regression results using alternative weighting specifications.

	SIDS (1)	Non SIDS (2)
Weight = exposed population		
Immediate effect, $L = 0$	-0.00017***	0.00002
	(0.00004)	(0.00010)
Marginal cum. effect, $L = 1$	-0.00016***	0.00006
	(0.00005)	(0.00010)
Marginal cum. effect, $L = 5$	-0.00021***	0.00007
	(0.00006)	(0.00013)
Marginal cum. effect, $L = 10$	-0.00027***	-0.00026
	(0.00009)	(0.00016)
Marginal cum. effect, $L = 15$	-0.00035***	-0.00048**
	(0.00011)	(0.00020)
No monthly weight at period 0		
Immediate effect, $L = 0$	-0.00008***	0.00002
	(0.00002)	(0.00004)
Marginal cum. effect, $L = 1$	-0.00005*	0.00009
	(0.00003)	(0.00006)
Marginal cum. effect, $L = 5$	-0.00010**	0.00011
	(0.00005)	(0.00010)
Marginal cum. effect, $L = 10$	-0.00016**	-0.00006
	(0.00008)	(0.00014)
Marginal cum. effect, $L = 15$	-0.00020**	-0.00034*
	(0.00010)	(0.00020)
Monthly weight extended until lag 3		
Immediate effect, $L = 0$	-0.00016***	0.00012
	(0.00004)	(0.00011)
Marginal cum. effect, $L = 1$	-0.00013***	0.00020
	(0.00005)	(0.00013)
Marginal cum. effect, $L = 5$	-0.00018***	0.00023
	(0.00007)	(0.00016)
Marginal cum. effect, $L = 10$	-0.00021**	3.36e-06
	(0.00009)	(0.00020)
Marginal cum. effect, $L = 15$	-0.00025**	-0.00028
	(0.00011)	(0.00024)

Notes: Estimations with outlier-robust regression. Standard errors incorporating the Street & al. (1988) correction are in parentheses. Time and country fixed effects, as well as temperature and precipitation controls are included in all specifications, but not reported in the table.
Significance levels : *** 1 % ; ** 5 % ; * 10 %.

Alternative panel specifications

Thus far, results obtained for SIDS are consistent with the neoclassical growth theory in the very short-run as it predicts an immediate negative impact on economic growth and a slight recovery one period later. The growth loss is often explained by the potential destruction of capital stock or employment caused by the disaster. Then, after the occurrence of the disaster, theory predicts a gradual return to a stable steady state level of output *per capita*, and thus, a temporary increase in growth.[15] Accordingly, the results' sensitivity is further analyzed by including some determinants of growth in the main specification. However, as recalled by Dell & al. (2014), one should be cautious when including control variables that are themselves outcomes of cyclone events as it will induce an "over-controlling problem". The addition of economic control variables can prevent from estimating the true net effect of cyclone events on output, as cyclones surely have an impact on these variables, which in turn impact the dependent variable.[16] To limit this concern, lagged values of control variables are used. Following Solow (1956) but also Mankiw & al. (1992) and Islam (1995), logarithmic lagged values of *per capita* GDP, population, *per capita* investment and trade openness are included to the main model. According to the Solow growth model, the lagged value of *per capita* GDP captures the rate of convergence towards the steady state.[17] Table 2.7 reports the results from this change in the specification in column 3. It also shows results from a regression that includes region $\times$ year and SIDS $\times$ year fixed effects in column 2. Including region $\times$ year fixed effects is a way to control for spatiotemporal trends. Thus, this estimation investigates concerns about the spurious relationship when spatially correlated outcomes such as growth variables are regressed on meteorological variables, *i.e.* cyclone intensity, temperature or rainfall, which are spatially correlated too (Lind, 2019). Column 4 re-estimates equation (2.3) when including Standardised Precipitation-Evapotranspiration Index (SPEI) as a control variable in addition to temperature and precipitation. SPEI index is a drought index constructed from CRU TS dataset, so it is available for each 0.5° latitude $\times$ 0.5° longitude pixel worldwide monthly since 1901. For the 83 sample countries, the indicator ranges between -2.3 to +1.5, negative values meaning dryness and positive ones meaning wetness. The main advantage of this drought indicator is to properly consider potential evapotranspiration, which is he potential evaporation from soils and plant transpiration. Finally, column 5 presents the estimations when using Conley (1999) standard errors, which are robust to spatial dependence between countries and serial correlation. To ease comparisons, main results presented in Table 2.4 are repeated in column 1.

With additional control variables (column 3), cumulative effects' significance are lessened for SIDS. In the case when $L = 15$, estimates become non-significant after period 8 for SIDS, and are statistically significant after period 10 for non SIDS. The magnitude of these coefficients also varies: the time path of the effects in SIDS becomes a straight line. This result highlights three core aspects. It confirms the exogeneity of the cyclone indicator as estimates are of same magnitude given 95% confidence bands. Then, it confirms that lag structures are not particularly influential and short-term effects are most decisive. Third, the negative sign associated with the lagged value of *per capita* GDP shows that

[15]Concerning this specific point, several interpretations can be found in the literature. The expected positive effect on growth is mainly explained by budgetary impulses intending to replace the destroyed capital stock. Among others, Skidmore & Toya (2002) argue that disasters stimulate innovation, while Caballero & Hammour (1994) or Crespo Cuaresma & al. (2008) support that the faster growth is related to the replacement of the destroyed physical capital, potentially old and outdated, by newer and more efficient equipment.

[16]Economic controls can therefore be considered as "bad controls" (Angrist & Pischke, 2009).

[17]In case of convergence, the estimated coefficient should be negative. See Acemoglu (2007) for a detailed discussion.

the economy is still converging towards its steady-state level after the cyclone strike. Point estimates from column 2 and column 3 are fairly comparable in terms of statistical significance for both sub-samples. Estimates are once again non-significant for SIDS in the very long-run with the 15 lags model. Results reported for non SIDS are intermittently significant in final periods when including additional fixed effects. Still, across all different lag specifications, the estimated coefficient for period 0 remains non-significant.[18] These results for non SIDS are consistent with previous findings as statistical significance varies widely across specifications and does not provide a sufficient basis for any general conclusion. Incorporating a control for local atmospheric conditions with the SPEI index (column 4) does not change the results, even though standard errors slightly increase compared to column 1 as the number of observations is reduced. Finally, running regressions using Conley's (1999) standard errors shows a statistically significant positive impact in the short run for non SIDS (column 5). However, this result must be interpreted with caution as the immediate effect's significance vanishes across all estimations when including lagged values of cyclone intensity. As additional specification checks, Appendix E-Table E.2.1 reports regressions when keeping the same number of observations as the baseline specification with $L = 15$, while Table E.2.2 re-estimates equation (2.3) when all the countries affected by extratropical cyclones only are excluded from the sample.[19] In no case are the estimates significant for non SIDS, while results remain in line with those obtained above for SIDS. Then, Table E.2.3 examines the effect of the interaction between the cyclone indicator and the annual number of cyclones. This newly created indicator considers both the frequency and intensity of tropical cyclones. As expected from previous discussions in section 2.3 and results presented in section 2.4.2, cyclone frequency amplifies growth losses for SIDS and non SIDS, but as for non SIDS, results are only significant in the very-long run, for $L = 10$ or $L = 15$. Appendix E - Table E.2.4 reconsiders the main estimator, and instead, exploits the difference in differences estimator developed by De Chaisemartin & D'Haultfoeuille (2020). This estimator is robust to heterogeneous treatment effects across countries as it is the case in this article. Their point is that coefficients obtained from a linear regression that includes fixed effects can be reversed due to negative weighting in the summation process of weighted average treatment effect in each country and period when the timing of the treatment differs for each country. This alternative indicator's computation is limited to the immediate effect, and results remain consistent with previous ones in terms of statistical significance for SIDS and non SIDS, but reverses the coefficient sign for non SIDS. Alternatively, we examine whether results are altered when restricting the sample to small countries only (Table E.2.5). In fact, it might be the case that only small countries are adversely affected by tropical cyclones as the exposure within their countries is more likely to be homogeneous. Hence, we keep all the countries having an area smaller than Papua New Guinea, which is our largest SIDS. Reconsidering the sample in this way does not change the results either. In Table E.2.6 and Table E.2.7, we respectively try for a binary indicator of cyclone occurrence in SIDS and a quadratic specification. Both of these estimations increase the magnitude of the coefficients, but greatly reduce statistical

[18]Results are also similar to those presented in column 1 when including time-trends only.

[19]This set of countries corresponds to Algeria, Canada, France, Iceland, Ireland, Morocco, Norway, Portugal, Russia, Spain, and United Kingdom.

significance, except for the immediate effect in the latter case. Finally, Figure E.2.1 reports the distribution of point estimates of the immediate effect on SIDS that is obtained when randomly changing the timing of the cyclones within countries. 10 000 different regressions are run in which each country's tropical cyclone time-series is re-ordered randomly. As the distribution is centered at 0, this placebo test confirms that the result obtained with the actual data, indicated by a vertical line (-0.00016, significant at the 1% level), cannot be biased.

Table 2.7: Regression results using alternative panel specifications.

	Main Model Specification (1)	Additional Fixed Effects (2)	Additional Control Variables (3)	Meteorological controls + SPEI index (4)	Using Conley (1999) Standard Errors (5)
Model with no cyclone lag: immediate effect					
$ln(GDP\ per\ capita)_{i,t-1}$			-0.01216***		
			(0.00312)		
$\overline{Cyc}_{i,t}$	0.00012	0.00019	0.00008	0.00017	0.00027**
	(0.00011)	(0.00012)	(0.00011)	(0.00012)	(0.00012)
$\overline{Cyc}_{i,t} \times SIDS$	-0.00028**	-0.00034***	-0.00024**	-0.00034***	-0.00044***
	(0.00012)	(0.00013)	(0.00012)	(0.00013)	(0.00013)
$ln(Population)_{i,t-1}$			0.02637***		
			(0.00424)		
$ln(Trade\ Openness)_{i,t-1}$			0.00752***		
			(0.00187)		
$ln(Investment\ per\ capita)_{i,t-1}$			0.00393**		
			(0.00185)		
Observations	3676	3676	3629	3226	3676
Adjusted R^2	0.25	0.30	0.28	0.26	0.14
Immediate effect in SIDS	-0.00016***	-0.00015***	-0.00016***	-0.00017***	-0.00017***
	(0.00004)	(0.00005)	(0.00004)	(0.00005)	(0.00007)
Model with 1 cyclone lag:					
Marginal cumulative effect in SIDS	-0.00014***	-0.00013***	-0.00013***	-0.00016***	-0.00014***
	(0.00005)	(0.00005)	(0.00004)	(0.00005)	(0.00005)
Marginal cumulative effect in non SIDS	0.00017	0.00025*	0.00014	0.00018	0.00019*
	(0.00011)	(0.00013)	(0.00012)	(0.00013)	(0.00012)
Model with 5 cyclone lags:					
Marginal cumulative effect in SIDS	-0.00018***	-0.00012*	-0.00013**	-0.00015**	-0.00016**
	(0.00006)	(0.00007)	(0.00006)	(0.00007)	(0.00007)
Marginal cumulative effect in non SIDS	0.00019	0.00035**	0.00010	0.00009	0.00015
	(0.00015)	(0.00016)	(0.00015)	(0.00015)	(0.00013)
Model with 10 cyclone lags:					
Marginal cumulative effect in SIDS	-0.00022***	-0.00017*	-0.00013*	-0.00020**	-0.00013*
	(0.00008)	(0.00009)	(0.00008)	(0.00010)	(0.00008)
Marginal cumulative effect in non SIDS	-0.00003	0.00017	-0.00016	-0.00017	0.00014
	(0.00018)	(0.00020)	(0.00018)	(0.00019)	(0.00014)
Model with 15 cyclone lags:					
Marginal cumulative effect in SIDS	-0.00024**	-0.00015	-0.00013	-0.00017	-0.00017**
	(0.00011)	(0.00011)	(0.00010)	(0.00013)	(0.00008)
Marginal cumulative effect in non SIDS	-0.00029	-0.00050**	-0.00045**	-0.00034	0.00014
	(0.00022)	(0.00025)	(0.00022)	(0.00023)	(0.00012)

Notes: Columns 1 to 4 present outlier-robust regression estimates with standard errors incorporating the Street & al. (1988) correction in parentheses. Time and country fixed effects, as well as temperature and precipitation controls are included in specifications (1) to (4), but not reported in the table. Additional fixed effects model includes Region × Year and SIDS × Year fixed effects. Column 5 presents OLS regression results with standard errors corrected for cross-sectional spatial dependence and panel-specific serial correlation as in Conley (1999). The spatial correlation cutoff is 1000km, and the serial correlation one is 3 lags.

Significance levels : *** 1 % ; ** 5 % ; * 10 %.

2.5 Tropical cyclones, an impediment to sustainable growth in small island developing states

Previous estimations infer a persistent negative growth effect of tropical cyclones in SIDS and suggest further investigation on the underlying mechanisms leading to this result. It is proved that national growth effects are heterogeneous across countries, especially for those combining small size and lower development level such as SIDS. This may be explained by structural factors of vulnerability, such as the concentration of activity over a reduced surface or the lack of spatial heterogeneity in terms of cyclone exposure at national scale.

In what follows, economic and physical channels are explored. First, SIDS' degree of dependence on international markets after a cyclone strike is analyzed. Then, effects on their rebuilding capacities are examined using *per capita* investment and sectoral GDP growth for the construction industry. According to neoclassical growth theory, *per capita* investment is fundamental to explain the absence of sustained recovery. Finally, the adaptive behavior of SIDS to tropical cyclones is analyzed by repeating the main specification on those most frequently exposed to this shock.

2.5.1 Exposure to foreign economic conditions

Given the particularity of SIDS' geographical situation and economic issues, it is essential to study the transmission channels using indicators that are specifically designed for this subgroup of countries. In this sense, Briguglio (1995) developed an index based on major sources that render SIDS economies vulnerable to forces outside their control, *i.e.* their small size, remoteness, insularity and proneness to natural disasters. To take advantage of this work, the main empirical strategy (equation (2.3)) is first applied to one of the variables included in this index: the degree of exposure to foreign economic conditions, which is calculated as the mean volume of exports and imports relative to GDP. Mathematically, it is expressed as follows:

$$Exposure_{i,t} = \frac{Imports_{i,t} + Exports_{i,t}}{2 \times GDP_{i,t}}$$

The relevance of using this dependent variable additionally lies in the fact that previously observed negative effects on economic activity might be triggered by a negative effect on a combination of determinants of growth and not necessarily by distinct impacts on each of them. This point is supported by complementary estimations made on export growth or import growth. Overall, point estimates suggest that trade is negatively affected in the short run, though these effects are insignificant. We find no significant immediate effect on exportation but positive and statistically significant dynamics in the long run. As for imports, we find a negative immediate effect with a positive leap one period after. Results on imports consistently remain insignificant.[20]

Figure 2.5 plots the cumulative growth response of Briguglio's (1995) economic exposure indicator with $L = 15$. On impact, SIDS economies' dependence on foreign exchanges

[20] Results available upon request.

is significantly increased. After the strike, this dependence remains increased for 5 years, with point estimates significant at the 10% level for periods 0 and 5, and at the 5% level for all periods between 1 and 4. One additional km/h of cyclone intensity is associated with a 0.03 percentage points increase of economic exposure growth five years after a cyclone strike. Thus, the immediate negative effect observed on economic growth and the absence of subsequent recovery in the short-run is linked with this result, as SIDS are strongly dependent on foreign exchange earnings or on the importation of basic supplies that cannot be produced domestically. This increase in economic vulnerability is emphasized by additional results on the impact on tourism receipts growth reported in Appendix Figure F.2.1. These additional results suggest that tourism receipts growth, which represents one of SIDS' main revenue sources is, on impact, negatively affected by cyclone strikes. Losses of tourism receipts persist in the short-run as the cumulative effect remains significant up to five years after a strike. However, these adverse impacts on SIDS economies should be put in perspective, as it is still likely that some financial flows can display countercyclical effects. For instance, remittances show positive growth dynamics for 15 years after a cyclone strike, though these effects are mostly insignificant (Appendix Figure F.2.2).[21]

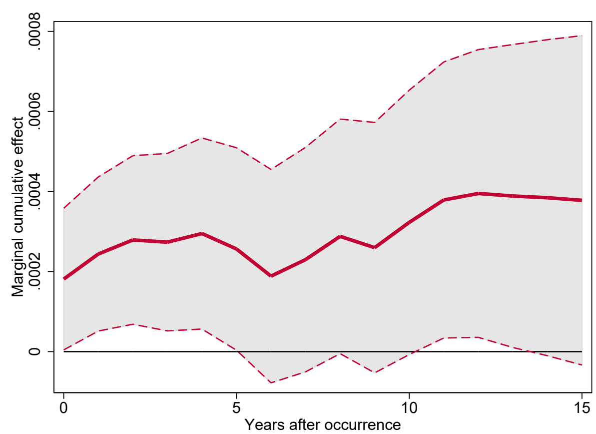

Figure 2.5: Measures of the marginal cumulative effects over fifteen years of cyclone events on Briguglio's (1995) economic exposure index growth for small island developing states.
Notes: Estimations with outlier-robust regression. Standard errors are computed using the Street & al. (1988) correction. Shaded areas represent the associated 90 % confidence intervals.

2.5.2 Hurdles to recover

The main panel methodology is then applied to explore the effects of tropical cyclones on *per capita* investment growth as well as sectoral GDP growth for the construction industry. *Per capita* investment is at the forefront of growth theories. For instance, according to the Solow-Swan model, it brings on capital accumulation, while in an endogenous growth framework, it stimulates technological progress. In such models, when a storm destroys a share of capital stock, the economy may return to its steady state by raising *per capita*

[21]As the data on tourism receipts or remittances are extracted from the WDI database, which is an alternative economic data source, the number of observations is drastically diminished in both of these estimations and the associated results should be interpreted with care.

investment growth. As for the construction sector, it is positively impacted in related world base, regional, national-level analyses (Hsiang & Jina, 2014; Hsiang, 2010; Zhou & Zhang, 2021), or even in local single-event studies (Vigdor, 2008). In particular, it is used to bring evidence for a creative destruction scenario, as damages from cyclones trigger opportunities for reconstruction.

Results are presented in Figure 2.6, and show consistency with previous findings on *per capita* GDP growth. Point estimates are almost always non-significant for both variables, suggesting that institutional responses brought after a storm shock are limited in SIDS. The absence of an immediate and cumulative increase in *per capita* investment growth can be explained by their incapacity to increase their debt level to finance reconstruction and implement a clear-cut recovery plan. In 2015, SIDS had, on average, a greater debt-to-GNI ratio than other developing countries (OECD, 2018). These higher levels of public debt limit fiscal scope for governments to make appropriate investments for risk mitigation or, more generally, for development. This point is further investigated in Appendix F, where the absence of any significant effect (immediate and cumulative) of tropical cyclones on SIDS' debt-to-GDP ratio or international aid growth is demonstrated in Figure F.2.2 and Figure F.2.3 respectively, even though coefficients are positive in the short-run. No positive shift in investment growth patterns also suggests that cyclones may be a factor of deterrence for private investors, which seems to be confirmed by the negative and significant long-run effect estimated on SIDS' private investment-to-GDP ratio presented in Figure F.2.4.[22] Alternatively, these results can be explained by budget or fund reallocation processes, as shown in Benson (1997) after cyclone Kina in Fiji in 1993. Tropical cyclones may divert investments that would otherwise foster growth. Interpreting this absence of leap in investment with the previous result obtained in section 2.4.2 when lagged value of *per capita* GDP is included in the model, the Solow growth model predicts that convergence towards the steady-state is maintained but not accelerated after a cyclone strike. Reaching the steady-state is simply delayed in time. Then, findings on construction sector growth suggest that SIDS' reconstruction capacities are low. The obtained results differ from those observed in the existing literature, as no significant positive effect is found for 15 years.[23] SIDS' narrow resource base might explain this absence of impact. Such incapacity to respond positively in the aftermath of a tropical cyclone might, in turn, lead to shoddy or incomplete rebuilding work between each disaster event.

[22]However, as all data used to construct these three figures are once again extracted from WDI database, meaning that the number of observations is still drastically diminished.

[23]Although Hsiang (2010) finds a positive impact using a sample of Caribbean and Central American countries, which is mostly composed of SIDS, these countries only represent about 50% of the present sample. For instance, small islands located in the Pacific are often more isolated than other countries, which increases even more their lack of domestic economic production (Tisdell, 2007).

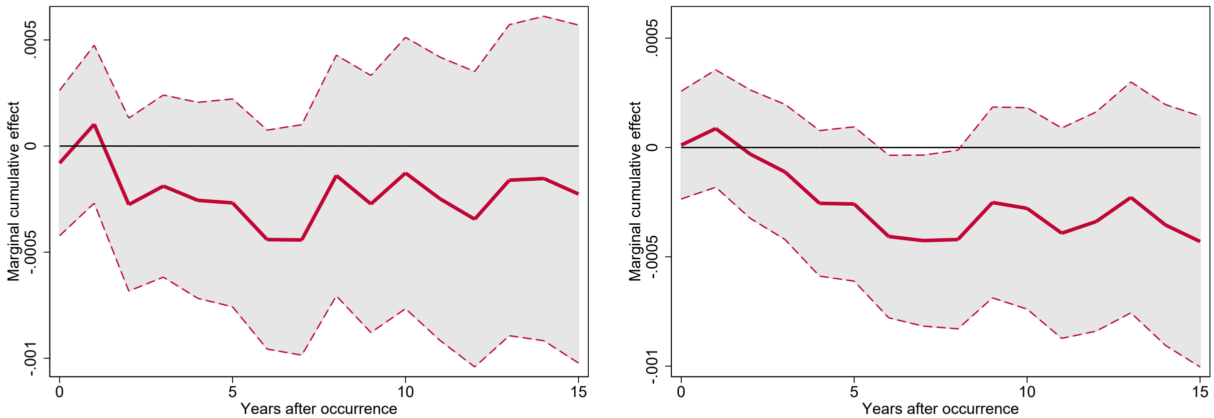

Figure 2.6: Measures of the marginal cumulative effects over fifteen years of cyclone events on *per capita* investment growth (left-hand side) and construction industry growth (right-hand side) for small island developing states.
Notes: Estimations with outlier-robust regression. Standard errors are computed using the Street & al. (1988) correction. Shaded areas represent the associated 90 % confidence intervals.

2.5.3 Does the frequency of events matter?

SIDS' ability to adapt to cyclone events is examined by distinguishing those that are more prone to these hazards. A SIDS is considered as frequently hit if it has known an above median number of cyclone events among the entire set of SIDS from 1950 to 2015. This median threshold corresponds to 0.42 cyclones per year. No significant difference in means is found between the most frequently hit SIDS' and other SIDS' *per capita* GDP, meaning that those most frequently hit are not the poorer countries. Figure 2.7 compares the marginal cumulative effects of one additional km/h of intensity shock on frequently hit SIDS' and other SIDS' economic growth. Overall, estimates of short- to long-term impacts are larger in magnitude for SIDS if they are repeatedly hit by cyclones, but statistical differences are not significant.[24] The absence of enhanced growth dynamics suggests that SIDS struggle to implement adaptation policies. In fact, one might expect that countries more prone to disasters have more incentives to invest in mitigating measures so that the economic impact is reduced *in fine*. The obtained results rather demonstrate that difficulties in restraining losses persist for frequently affected SIDS. This point is even more concerning in regard to alterations expected in tropical cyclones' frequency, intensity or duration due to climate change (IPCC, 2019). The present results combined with those on *per capita* investment and construction industry growth additionally infer the risk of poverty traps due to cyclone strikes. This risk is even greater when the frequency of storm events is high. The more tropical cyclones hit a SIDS, the more it is unable to fully rebuild between each catastrophe. These SIDS may end up remaining in a continuous stage of reconstruction (Hallegate & Dumas, 2009).

[24] A similar analysis is conducted for non SIDS countries (Appendix F - Figure F.2.5) and shows a significant difference in the very long-run cumulative effects for non frequently hit countries. In particular, it reveals that the significant negative results observed after period 10 in some of the estimations presented in section 2.4.2 are mainly due to non frequently hit non SIDS.

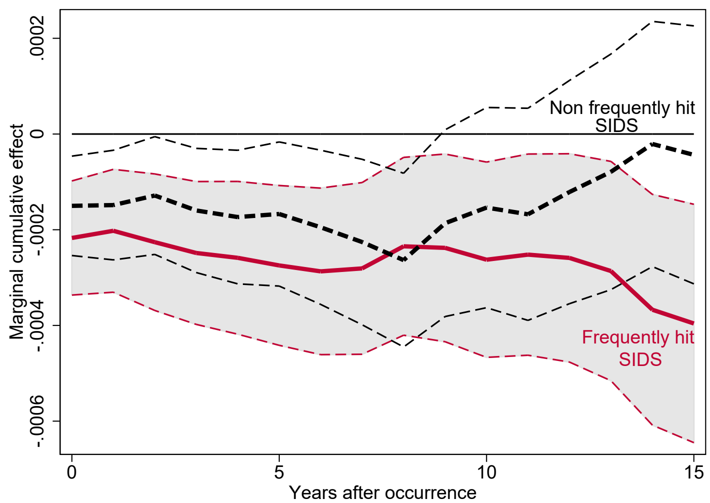

Figure 2.7: Measures of the marginal cumulative effects over fifteen years of cyclone events on *per capita* GDP growth for frequently hit small island developing states.
Notes: Estimations with outlier-robust regression. Standard errors are computed using the Street & al. (1988) correction. Shaded areas represent the associated 90 % confidence intervals obtained for frequently hit states. Black dashed lines correspond to the estimations for the complementary subgroup of non frequently hit small island developing states (SIDS).

2.6 Are there any permanent effects on economic activity?

Previous sections inform us on the existence of persistent effects over 15 years of tropical cyclones on national economic growth in SIDS. Yet, one question remains to be clarified: are these effects permanent? To briefly explore this question, we remain in the class of distributed lag models, but try another specification with infinite lags.

To begin with, we recall that such a general distributed lag model applied to our research question and setting can be written:

$$g_{i,t} = \alpha + \sum_{j=0}^{\infty} \beta_j \overline{Cyc}_{i,t-j} + \mu_i + \eta_t + \varepsilon_{i,t} \tag{2.4}$$

With $\varepsilon_{i,t}$ a white noise error term. In this case, the long-run effect of tropical cyclones on economic growth corresponds to $\sum\limits_{j=0}^{\infty} \beta_j$. Thus, the key issue is to determine the value of this summation, meaning that this series is should be convergent. We understand that in order to compute permanent effects, the model should lie on assumptions that render the summation convergent to a real value. One solution is to define β_j as:

$$\beta_j = \beta_0 \lambda^j, \quad \begin{cases} j = 0, 1, 2, ... \\ \lambda \in]0; 1[\end{cases}$$

Such a definition of an infinite distributed lag model corresponds to the *Koyck approach*. It implicitly assumes that the impact is continuously declining as time goes by, following a geometric progression *via* the λ parameter, which is called the rate of decline.

Hence, the equation of interest can be rewritten:

$$g_{i,t} = \alpha + \sum_{j=0}^{\infty} \beta_0 \lambda^j \overline{Cyc}_{i,t-j} + \mu_i + \eta_t + \varepsilon_{i,t} \tag{2.5}$$

In accordance with the original model (equation (2.4)), we have that:

$$\sum_{j=0}^{\infty} \beta_j = \beta_0 \left(\sum_{j=0}^{\infty} \lambda^j \right) = \beta_0 \frac{1}{1-\lambda}$$

With $(1-\lambda)$ known as the speed of adjustment.

Now, let us try to derive an auto-regressive form based on the distributed lag model. First, we have that:

$$\lambda g_{i,t-1} = \lambda\alpha + \lambda\beta_0 \sum_{j=0}^{\infty} \lambda^j \overline{Cyc}_{i,t-1-j} + \lambda\mu_i + \lambda\eta_{t-1} + \lambda\varepsilon_{i,t-1}$$

$$\iff \lambda g_{i,t-1} = \lambda\alpha + \lambda\beta_0 \overline{Cyc}_{t-1} + \lambda^2 \beta_0 \overline{Cyc}_{t-2} + ... + \lambda\mu_i + \lambda\eta_{t-1} + \lambda\varepsilon_{i,t-1}$$

Subtracting it to equation (2.5), we get:

$$g_{i,t} - \lambda g_{i,t-1} = \alpha(1-\lambda) + \beta_0 \overline{Cyc}_t + (1-\lambda)\mu_i + (\eta_t - \lambda\eta_{t-1}) + (\varepsilon_{i,t} - \lambda\varepsilon_{i,t-1})$$

$$\iff g_{i,t} = \lambda g_{i,t-1} + \alpha^\star + \beta_0 \overline{Cyc}_t + (1-\lambda)\mu_i + \delta_t + \nu_{i,t}$$

With $\nu_{i,t} = \varepsilon_{i,t} - \lambda\varepsilon_{i,t-1}$, and $\delta_t = \eta_t - \lambda\eta_{t-1}$. This procedure is known as the *Koyck transformation*, and the aim is to determine the parameters $\alpha^\star$, β_0 and λ.

As in the previous specification, we also include a controls for temperature and precipitation. In addition, as $T = 46$, issues regarding the Nickell bias are avoided (Judson & Owen, 1999). Finally, one limitation with this model is the impossibility to include the temporal weight as Noy (2009) for the contemporaneous impact, as the structure of the model depends on a unique type of independent variable.

Table 2.8: Regression results, permanent effects of tropical cyclones on economic growth

	Whole sample (1)	SIDS only (2)	Non SIDS only (3)
$\Delta ln(GDPpc)_{i,t-1}$	0.258***	0.187***	0.299***
	(0.030)	(0.046)	(0.038)
$\overline{Cyc}_{i,t}$	-0.00007**	-0.00009**	-0.00002
	(0.00003)	(0.00004)	(0.00005)
Observations	3593	1256	2337
Adjusted R^2	0.17	0.11	0.22
Long-run (equilibrium) effect	-0.00010**	-0.00011***	-0.00002
	(0.00004)	(0.00005)	(0.00007)

Notes: Panel data regression estimates. Robust standard errors are in parentheses. Time and country fixed effects, as well as temperature and precipitation controls are included in all estimations, but not reported in the table. Long-run effects are computed using the "nlcom" procedure in Stata. Significance levels : *** 1 % ; ** 5 % ; * 10 %.

Table 2.8 outlines the results. Short-run effects (β_0, *i.e.* coefficient of $\overline{Cyc}_{i,t}$) are almost identical to those observed when removing the monthly weight in section 2.4.2, although the standard errors in the second and third column increase a bit, as one might expect given that we have reduced the amount of data in the model. The estimated immediate effect for the world sample remains negative, with a -0.007 percentage point growth loss for each additional km/h of cyclone intensity over a country. The analysis of long-run effect estimates are interesting as it confirms the hypothesis of a quasi-constant effect over time for SIDS, and the absence of significant effect in non SIDS. As for the whole sample, the downward trajectory observed over 15 years in the baseline results is not counteracted either in the long-run, as the permanent effect is of same magnitude than the immediate effect. In all cases, the scenario of a "catch-up" is excluded, and the adverse effects observed in first periods are the most informative. Even though the Koyck transformation relies on a geometrical distribution of lags, the present estimates remain in line with those obtained so far. Having said that, assuming a stronger impact of tropical cyclones on economic activity in recent periods compared to successively distant ones does not seem unreasonable. In order to provide more external validity to these results, it might be interesting in the future to explore other types of infinite distributed lag models.

2.7 Concluding remarks

This paper investigates the impact of cyclone events on economic growth for 83 nations worldwide during the period 1970-2015. First, a set of exogenous weather indicators is built at the pixel level using geophysical and meteorological datasets. A special focus is made on SIDS, which are of particular interest as they are expected to be more vulnerable to natural disasters, especially due to their small size and low level of development. Beyond an inequality of exposure to tropical cyclones between SIDS and non SIDS, evidence is brought for differentiated impact between these two groups of countries. Tropical cyclones increase SIDS' economic vulnerability, whereas they are not disruptive enough to be reflected in non SIDS' national growth rates irrespective of their level of development. This differential impact may come from the fact that, in a SIDS, the entire economy and population are likely to be concerned by these shocks. In contrast, in a non SIDS, this might not be the case and the present study provides support for more micro-scaled research, eventually at county or regional level as in Strobl (2011). Non SIDS may have only small parts of their respective territories that are highly vulnerable to tropical cyclones, and our results suggest that conducting subnational-level analyses would be far more adequate in these countries. All in all, a one km/h increase of cyclone intensity over a SIDS is responsible for a 0.024 percentage points cumulative growth loss 15 years later. Expressed differently, a one standard deviation increase in the cyclone intensity indicator is associated with a 0.84 percentage points cumulative loss of national growth 15 years later.

Short-term results obtained for SIDS appear very robust and are in line with basic predictions of the neoclassical growth model. An immediate negative effect is observed due to the destruction of a share of the capital stock, followed by a slight recovery explained by the convergence towards a stable steady-state. However, in no case response curves outperform the counterfactual scenario when no disaster occurs. Very long-run cumulative effects estimates are noisier given the specification but remain significant at least 8 years after a cyclone strike across all methods employed here. Additionally, it is proved that conclusions are not altered by the maximum lag length choice as long-run economic losses remain of same magnitude as time goes by. Related propagation mechanisms are documented through economic and physical channels. First, a specific vulnerability variable designed for SIDS is exploited, namely the extent of exposure to foreign economic conditions (Briguglio, 1995). Cyclone events substantially increase SIDS' short-run dependence on foreign markets, which counteracts the first signs of recovery triggered at period 1 and maintains the adverse impacts observed on economic growth. Then, further investigation on investment *per capita* and sectoral GDP growth for the construction industry also sheds light on their low reconstruction capacities and difficulties in pinning down crucial investment decisions at national scale. This second strand of results also suggests that SIDS' tight debt constraints prevent them from implementing a proper fiscal stimulus plan following a storm. Finally, the influence of the frequency of events is discussed by evaluating growth impacts on the most frequently affected share of SIDS. Hurdles to adopt mitigating measures are detected as cyclone frequency does not attenuate growth losses. More importantly, this result contributes to debates over future impacts of climate change and warns of SIDS' potential destiny. Policy implications regarding the urge to invest in economic preparedness or early warning systems shall emerge from this study. In the last section, an exploration of the effects beyond 15 years using an alternative specification suggests that the persistent effects are likely to translate into permanent ones.

The study of all possible underlying mechanisms deserves more exploration and further impact evaluations are needed to understand the inferred growth loss fully. This article is intended to inform on SIDS' specific vulnerability to cyclone risks, but several other aspects remain to be explored in greater depth, like migrations or remittances. These output variables are essential to maintain SIDS' consumption levels and can display countercyclical responses even though investment is unaffected. The impact on transport costs, another variable of vulnerability suggested by Briguglio (1995) to stress SIDS' remoteness and insularity, could also be estimated. Last but not least, GDP poorly explains impacts on populations' welfare, purchasing power or inequality, which seem to be equally important regarding the resilience after a cyclone shock. This first set of findings should trigger the opportunity for further empirical and theoretical research.

Appendix of Chapter 2

A Additional descriptive statistics

Table A.2.1: National summary statistics for sample nations

Country	ISO	Average values from 1950 to 2015: Annual Cyclone Windspeed (by exposed land, in km/h)	Annual Number of Cyclones	Annual Mean Temperature (in °C)	Annual Precipitation Level (in mm)	Classification
Algeria	DZA	0.0	0.0	22.8	87.7	
Antigua & Barbuda	ATG	42.4	0.5	26.2	2363.9	SIDS
Australia	AUS	4.8	3.4	21.8	528.4	
Bahamas	BHS	62.1	1.1	25.1	1310.6	SIDS
Bangladesh	BGD	13.3	0.8	25.1	2573.7	
Barbados	BRB	33.7	0.4	26.3	2154.6	SIDS
Belize	BLZ	26.6	0.4	25.6	2195.5	SIDS
Brazil	BRA	0.0	0.0	25.2	1760.5	
Brunei	BRN	0.6	0.0	27.1	2787.6	
Cambodia	KHM	4.6	0.7	27.1	1890.9	
Canada	CAN	1.2	1.4	-5.0	530.3	
Cape Verde	CPV	18.5	0.4	23.5	418.5	SIDS
China	CHN	4.1	8.0	7.3	626.6	
Colombia	COL	0.2	0.2	24.7	2601.9	
Comoros	COM	10.9	0.1	25.8	1664	SIDS
Costa Rica	CRI	1.8	0.1	25.1	2883.2	
Cuba	CUB	38.7	1.1	25.5	1360.9	SIDS
Dominica	DMA	44.6	0.5	22.5	3602.1	SIDS
Dominican Republic	DOM	29.9	0.6	24.7	1418.7	SIDS
El Salvador	SLV	2.5	0.1	24.7	1732.2	
Fiji	FJI	26.8	0.4	24.6	2697.9	SIDS
France	FRA	0.2	0.1	11.2	859.6	
Grenada	GRD	24.8	0.2	26.9	1545.3	SIDS
Guatemala	GTM	9.1	0.5	23.7	2716.9	
Guinea	GIN	0.1	0.0	26.0	1685.3	
Guinea-Bissau	GNB	1.2	0.0	27.0	1636.5	SIDS
Haiti	HTI	34.1	0.5	25.1	1441.1	SIDS
Honduras	HND	14.9	0.5	23.8	1964.1	
Hong Kong SAR China	HKG	86.9	1.5	22.9	2264.3	
Iceland	ISL	3.6	0.1	2.2	1009.1	
India	IND	4.1	2.1	23.9	1069.7	
Indonesia	IDN	0.3	0.3	26.0	2743.4	
Iran	IRN	0.0	0.0	17.7	214.7	
Ireland	IRL	8.6	0.2	9.6	1145.5	
Jamaica	JAM	29.4	0.4	25.2	2092.0	SIDS
Japan	JPN	77	6.8	11.5	1694.2	
Laos	LAO	15.0	1.8	23.0	1820.8	
Madagascar	MDG	16.2	1.3	22.9	1471	
Malawi	MWI	0.0	0.0	22.2	1137.8	
Malaysia	MYS	0.6	0.1	25.7	2947.3	
Mauritius	MUS	28.2	0.4	22.7	1973.1	SIDS
Mexico	MEX	14.7	4.8	21.4	742.4	
Montserrat	MSR	41.2	0.5	25.3	2632.6	SIDS
Morocco	MAR	0.5	0.0	17.4	330.2	

Table A.2.2: National summary statistics (continued)

Country	ISO	Average values from 1950 to 2015				
		Annual Cyclone Windspeed (by exposed land, in km/h)	Annual Number of Cyclones	Annual Mean Temperature (in °C)	Annual Precipitation Level (in mm)	Classification
Mozambique	MOZ	2.5	0.3	24.1	1015	
Myanmar (Burma)	MMR	4.4	0.5	23.2	2092.6	
New Caledonia	NCL	38.8	0.8	22.3	1481.6	SIDS
New Zealand	NZL	1.6	0.1	10.6	1720.3	
Nicaragua	NIC	10.1	0.3	25.2	2357.2	
North Korea	PRK	6.7	0.4	6.0	1051.4	
Norway	NOR	0.2	0.0	1.9	1129.3	
Oman	OMN	1.8	0.1	25.8	95.0	
Pakistan	PAK	0.4	0.1	20.5	298.6	
Panama	PAN	1.6	0.0	25.6	2666.8	
Papua New Guinea	PNG	1.2	0.3	25.3	3129.4	SIDS
Philippines	PHL	105.1	7.4	26.0	2412	
Portugal	PRT	0.4	0.1	15.5	840.4	
Puerto Rico	PRI	36.4	0.5	25.5	2122.3	SIDS
Russia	RUS	0.1	0.6	-4.7	460.3	
Samoa	WSM	16.3	0.2	27.1	3024.8	SIDS
Saudi Arabia	SAU	0.0	0.0	25.1	74.5	
Singapore	SGP	1.8	0.0	26.8	2581.7	SIDS
Solomon Islands	SLB	17.5	0.5	25.7	3023.8	SIDS
Somalia	SOM	0.5	0.1	27.2	267.5	
South Africa	ZAF	0.0	0.0	18.1	483.4	
South Korea	KOR	40.1	1.2	11.9	1414.6	
Spain	ESP	0.7	0.1	13.7	620.1	
Sri Lanka	LKA	4.8	0.2	27.1	1705.2	
St. Kitts & Nevis	KNA	38.0	0.5	24.7	2188.6	SIDS
St. Lucia	LCA	36.3	0.4	25.7	2402.2	SIDS
St. Vincent & Grenadines	VCT	33.7	0.4	27.0	1614.2	SIDS
Tanzania	TZA	0.0	0.0	22.6	1032.4	
Thailand	THA	2.7	0.9	26.5	1628	
Timor-Leste	TLS	1.3	0.0	25.3	1443.2	SIDS
Tonga	TON	23.2	0.3	25.5	1972.6	SIDS
Trinidad & Tobago	TTO	11.6	0.1	25.9	1781	SIDS
United Kingdom	GBR	3.5	0.2	8.8	1248	
United States	USA	3.4	3.4	8.9	736.2	
Vanuatu	VUT	53	1.1	24.1	2785.3	SIDS
Venezuela	VEN	0.4	0.2	25.6	1877.2	
Vietnam	VNM	35.6	4.0	24.6	1812.2	
Yemen	YEM	0.4	0.1	24.0	158.1	
Zimbabwe	ZWE	0.5	0.0	21.4	685.4	

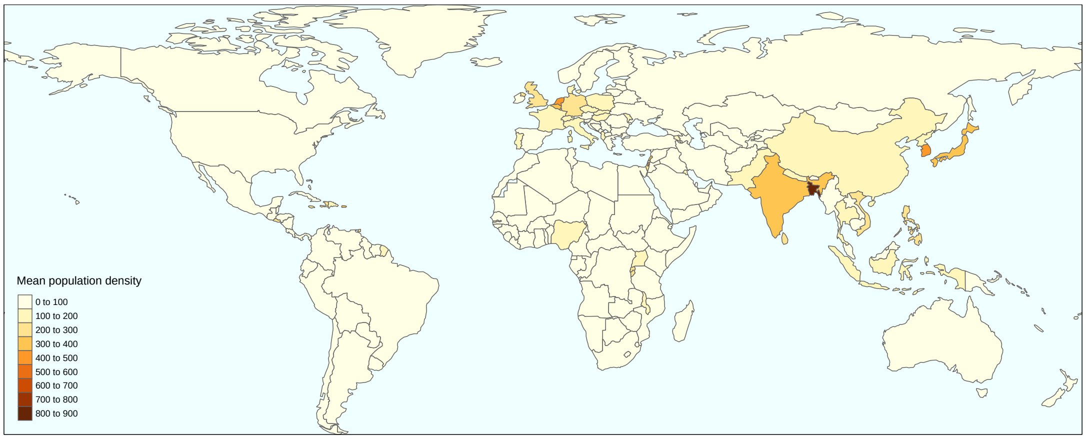

Figure A.2.1: Average population density for countries worldwide from 1970 to 2015

B Outlier-robust regression

Outlier-robust regression reveals to be of crucial importance in the case of estimations with data contaminated by extreme values. As a matter of fact, OLS estimations assume that errors are *i.i.d* with standard normal distribution, and thus, the presence of influential points can greatly deteriorate the efficiency of the estimation and generate misleading estimates. A wide range of robust regression techniques can be used, whether for detecting influential observations or estimating the coefficients of robust regression. Table B.2.1 presents usual indicators in influential observations detection: the leverage score, the studentized residual, Cook's distance and two indicators based on successive row deletions defined by Belsley, Kuh & Welsh (1980), $DFBETA$ and $DFFITS$. All of these indicators are estimated using the main identification strategy.

The leverage is a measure of the distance of a given observation's independent variable value from the rest of the observations in the sample. In other words, a high-leverage point is considered as an extreme value regarding the independent variables. It corresponds to the diagonal elements of the hat matrix. In the case of a perfectly balanced experimental design, we expect each observation to have the same leverage score. Then, the studentized residual corresponds to the value of the original residual divided by their respective standard error. Belsley, Kuh & Welsh (1980) define by *absolute cutoff* the threshold beyond which a diagnostic measure is large and observations can be considered as outliers. This threshold corresponds to two for studentized residuals. Influential observations can rather be detected by successive row deletions, *i.e.* by analysing the change in the estimated regression coefficients or fit when each row is successively deleted. This corresponds to the so-called $DFBETA$ or $DFFITS$. Finally, Cook (1977) suggested a similar measure for outliers detection. This measure is called Cook's distance, usually noted D, and estimated for each observation.

Table B.2.1: Influential observations statistics

	Observations	Min.	Median	Max.	Mean	Standard Dev.
Studentized res.	2556	-9.94	0.04	14.7	0.0001	1.01
Leverage points	2573	0.05	0.06	0.14	0.06	0.02
DFFITS	2556	-2.61	0.01	3.53	-0.00001	0.26
DFBETA($\overline{Cyc}_{i,t}$)	2556	-0.32	-0.00002	0.63	$-4.96 * 10^{-6}$	0.02
Cook's distance D	2556	$4.51 * 10^{-11}$	0.00008	0.07	0.0004	0.002

The outlier-robust regression corresponds to a so-called *M-estimation* and is described by Hamilton (1991a, 1992). M-estimators are specific weighted least-squares estimators designed to deal with dependent variable outliers (Y-outliers), unlike bounded-influence methods which deal with both dependent and independent variable outliers (X-outliers and Y-outliers). In this study, it seems reasonable to believe that also protecting against X-outliers would be absurd since the occurrence of a cyclone event, extreme temperatures or strong levels of precipitation is purely determined by the nature. Hence, the estimation of the outlier-robust regression is based on absolute residuals analysis and proceeds as follows. Firstly, a screening based on Cook's distance D is made and observations with $D > 1$ are dropped in order to eliminate gross outliers, as suggested by Cook & Weisberg (1982). Then, it calculates the weights to be attributed to each observation in the final regression by combining two weighting procedures: Huber weights (Huber, 1964) and biweights (Beaton & Tukey, 1974). These two weighting functions are complementary since Huber weighting shows weaknesses when dealing with severe outliers and biweighting can fail to converge or have multiple solutions (Li, 1985).

Without loss of generality, in a cross-sectional case, let $e_i = y_i - X_i\hat{\beta}$ be the residual of the i^{th} observation and $M = med(|e_i - med(e_i)|)$ the median absolute deviation from the median residual. Huber weighting provides:

$$w_i = \begin{cases} 1 & \text{if } |e_i| \leq 2M \\ 2M/|e_i| & \text{otherwise} \end{cases}$$

And the smoothly decreasing biweight function, calculated after Huber weights converge iteratively below a tolerance threshold (fixed by default at 0.01) is given by:

$$w_i = \begin{cases} [(1 - (e_i/7M)^2]^2 & \text{if } |e_i| \leq 7M \\ 0 & \text{otherwise} \end{cases}$$

This biweight threshold of 7 is called *tune*. Goodall (1983) states that the performance remains correct with a tune comprised between 6 and 12. Thus, a lower tuning constant implies a more drastic downweighting. In this study, none of the observations reach the threshold for Cook's distance D and 62 observations (out of 2556 observations) are muted by biweighting. Increasing the tuning constant diminishes the number of excluded observations and has barely any effect on the estimated coefficients and their respective statistical significance (see Appendix C - Figures C.2.2 and C.2.3).

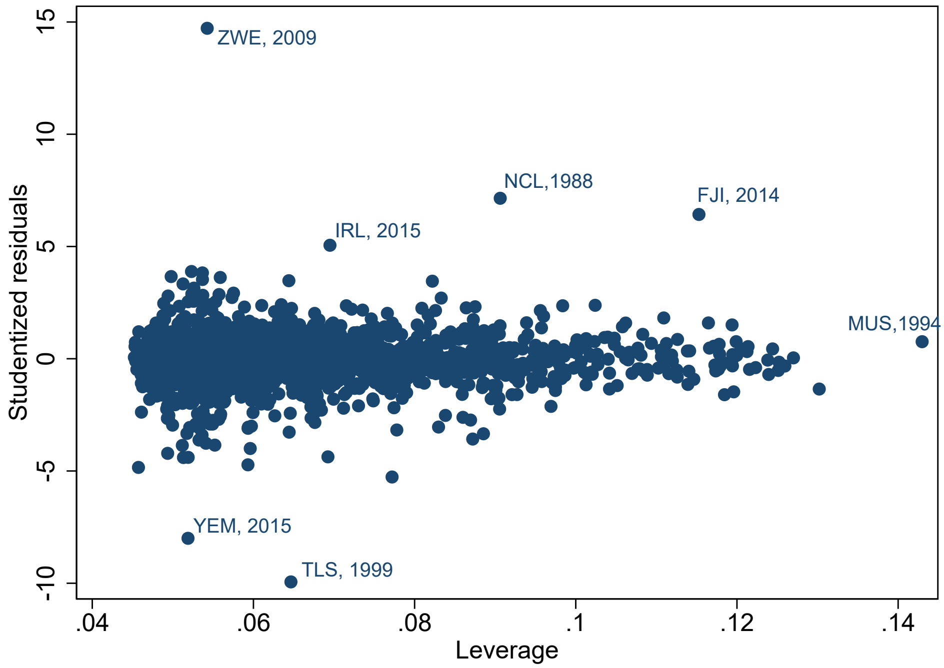

Figure B.2.1: Influential observations analysis.
Notes: The graph presents studentized residuals (Y-axis) calculated for each observation included in the main outlier-robust regression specification, plotted against their respective leverage point estimate (X-axis).

C Estimation on worldwide sample and detailed coefficients for main results

Table C.2.1 presents results from estimating equation (2.1) without lag, with one lag, five lags, ten lags or fifteen lags. Marginal cumulative effect estimates are shown on the bottom row of the table. Figure C.2.1 examines the cumulative effect on *per capita* GDP growth from a cyclone strike at time 0 when $L = 15$. In the year when the disaster occurs, one additional km/h of wind speed intensity over a country decreases growth by 0.013 percentage points. Across all lag horizon choices, the null hypothesis that cyclones have no immediate effect on growth is rejected at the 1% level. The estimated long-run cumulative effect is also significantly negative: growth losses accumulate to -0.029 percentage points after 15 years. These estimates imply that a one standard deviation ($\sigma_{\overline{Cyc}_{i,t}} = 35.1$) increase in the cyclone measurement is associated with a reduction in growth of 1.0 percentage point 15 years later. Hence, on the global scale, economic growth is sensitive to cyclone events as the sum of significant coefficients progressively declines over 15 years after a strike and remains below the counterfactual trajectory. This result is well in line with the existing literature as it provides another evidence for the negative and persistent effect of cyclone events on economic activity for a worldwide sample (Felbermayr & Gröschl, 2014; Krichene & al., 2021). Detailed coefficients for the 15 lags model are presented in Table C.2.2.

Table C.2.1: Regression results, world sample.

	No lag	1 lag	5 lags	10 lags	15 lags
	(1)	(2)	(3)	(4)	(5)
$\overline{Cyc}_{i,t}$	-0.00012***	-0.00013***	-0.00014***	-0.00014***	-0.00013***
	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
$\overline{Cyc}_{i,t-1}$		0.00004**	0.00003	0.00003*	0.00001
		(0.00002)	(0.00002)	(0.00002)	(0.00002)
$\overline{Cyc}_{i,t-2}$			-0.00001	-0.00002	-0.00002
			(0.00002)	(0.00002)	(0.00002)
$\overline{Cyc}_{i,t-3}$			-9.17e-06	-0.00002	-0.00003
			(0.00002)	(0.00002)	(0.00002)
Observations	3676	3676	3356	2956	2556
Adjusted R^2	0.25	0.25	0.27	0.29	0.32
Marginal cumulative effect (Ω_L)	-0.00012***	-0.00009**	-0.00011**	-0.00020***	-0.00029***
	(0.00004)	(0.00004)	(0.00005)	(0.00007)	(0.00009)

Notes: Outlier-robust regression estimates. Standard errors incorporating the Street & al. (1988) correction are in parentheses. Time and country fixed effects, as well as temperature and precipitation controls are included in all specifications, but not reported in the table.
Significance levels : *** 1 % ; ** 5 % ; * 10 %.

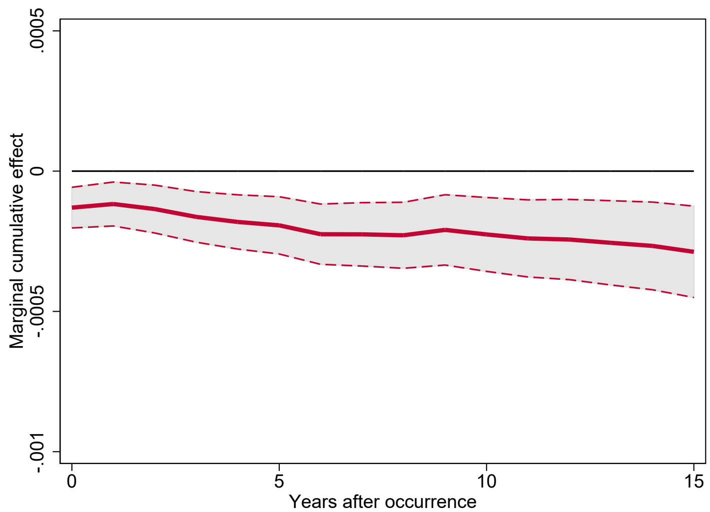

Figure C.2.1: Measures of the marginal cumulative effects over fifteen years of cyclone events on *per capita* GDP growth for the world sample

Notes: Estimations with outlier-robust regression. Standard errors are computed using the Street & al. (1988) correction. Shaded areas represent the associated 90 % confidence intervals.

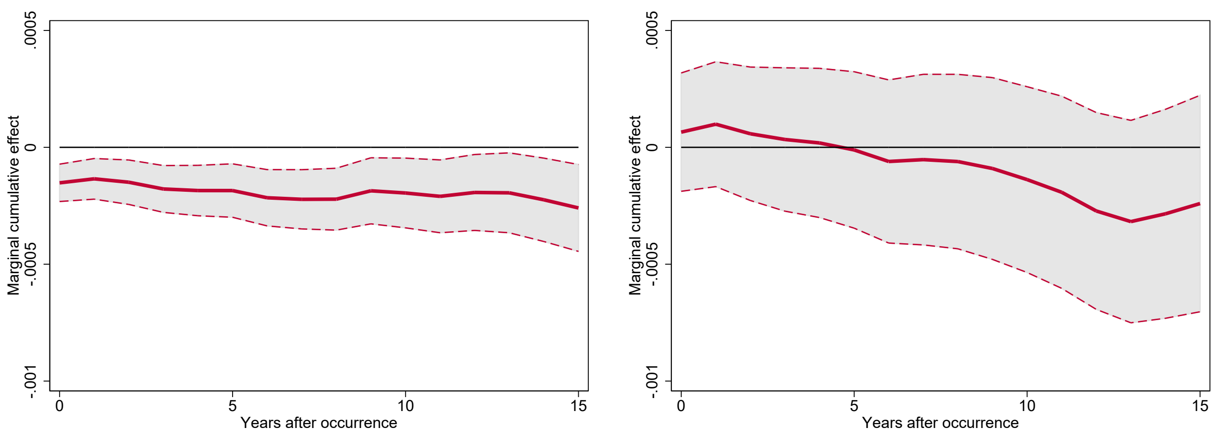

Figure C.2.2: Measures of the marginal cumulative effects over fifteen years of cyclone events on *per capita* GDP growth for the sample SIDS (left-hand side) and non SIDS (right-hand side).

Notes: Outlier-robust regression with tuning constant fixed at 9. Shaded areas represent the 90 % confidence intervals. 83 countries, $\overline{T} = 31$, 2556 observations (including 29 observations with weight 0).

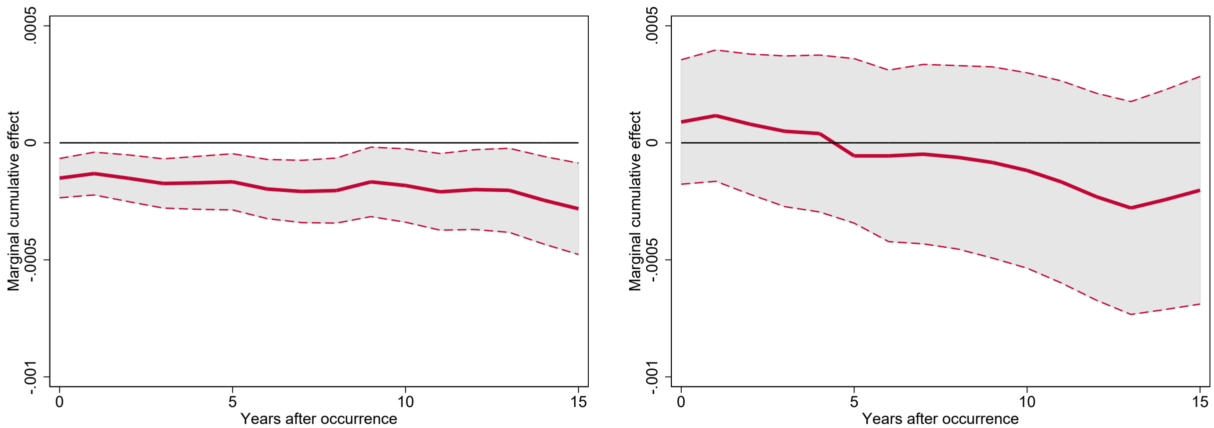

Figure C.2.3: Measures of the marginal cumulative effects over fifteen years of cyclone events on *per capita* GDP growth for the sample SIDS (left-hand side) and non SIDS (right-hand side). *Notes:* Outlier-robust regression with tuning constant fixed at 12. Shaded areas represent the 90 % confidence intervals. 83 countries, $\overline{T} = 31$, 2556 observations (including 10 observations with weight 0).

Table C.2.2: Impact of cyclone events on *per capita* GDP growth. Detailed marginal cumulative coefficients with $L = 15$.

	World	SIDS	Non SIDS
Immediate effect, year 0	-0.00013***	-0.00016***	0.00006
	(0.00004)	(0.00005)	(0.00013)
Marginal cum. effect, 1 year	-0.00012**	-0.00014***	0.00009
	(0.00005)	(0.00005)	(0.00013)
Marginal cum. effect, 2 years	-0.00013***	-0.00015***	0.00004
	(0.00005)	(0.00006)	(0.00014)
Marginal cum. effect, 3 years	-0.00016***	-0.00018***	0.00001
	(0.00005)	(0.00006)	(0.00015)
Marginal cum. effect, 4 years	-0.00018***	-0.00019***	-0.00001
	(0.00005)	(0.00006)	(0.00016)
Marginal cum. effect, 5 years	-0.00019***	-0.00020***	-0.00004
	(0.00006)	(0.00007)	(0.00017)
Marginal cum. effect, 6 years	-0.00023***	-0.00022***	-0.00009
	(0.00007)	(0.00007)	(0.00017)
Marginal cum. effect, 7 years	-0.00023***	-0.00023***	-0.00008
	(0.00007)	(0.00007)	(0.00018)
Marginal cum. effect, 8 years	-0.00023***	-0.00023***	-0.00008
	(0.00007)	(0.00008)	(0.00018)
Marginal cum. effect, 9 years	-0.00021***	-0.00020**	-0.00011
	(0.00008)	(0.00008)	(0.00019)
Marginal cum. effect, 10 years	-0.00023***	-0.00020**	-0.00016
	(0.00008)	(0.00008)	(0.00020)
Marginal cum. effect, 11 years	-0.00024***	-0.00021**	-0.00022
	(0.00008)	(0.00009)	(0.00020)
Marginal cum. effect, 12 years	-0.00024***	-0.00019**	-0.00032
	(0.00009)	(0.00009)	(0.00021)
Marginal cum. effect, 13 years	-0.00025***	-0.00019*	-0.00037
	(0.00009)	(0.00010)	(0.00022)
Marginal cum. effect, 14 years	-0.00027***	-0.00020**	-0.00034
	(0.00010)	(0.00010)	(0.00022)
Marginal cum. effect, 15 years	-0.00029***	-0.00024**	-0.00029
	(0.00010)	(0.00011)	(0.00023)
Observations	2494	2494	2494
Adjusted R^2	0.32	0.32	0.32

Notes: Estimations with outlier-robust regression. Standard errors incorporating the Street & al. (1988) correction are in parentheses. Time and country fixed effects as well as temperature and precipitation controls are included in all specifications, but not reported in the table.
Significance levels : *** 1 % ; ** 5 % ; * 10 %.

D Impact of cyclone events on *per capita* GDP for other subgroups of the world sample

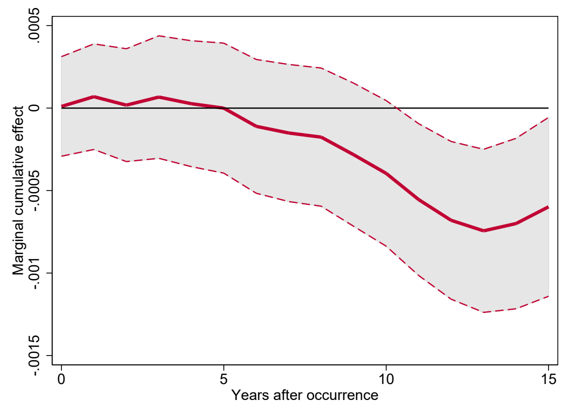

Figure D.2.1: Measures of the marginal cumulative effects over fifteen years of cyclone events on *per capita* GDP growth for the sample of developed countries.
Notes: Developed countries are defined as in the *World Economic Outlook 2000* database (International Monetary Fund). Estimations with outlier-robust regression. Standard errors are computed using the Street & al. (1988) correction. Shaded areas represent the associated 90 % confidence intervals.

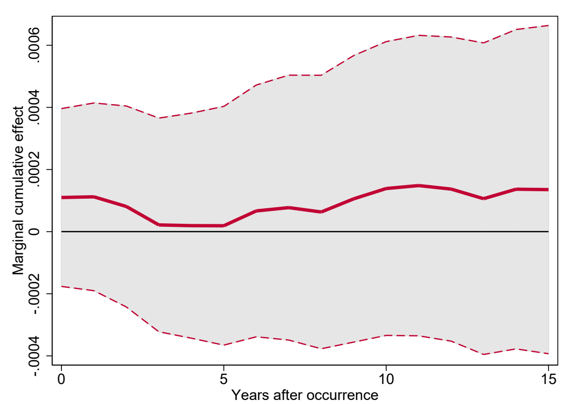

Figure D.2.2: Measures of the marginal cumulative effects over fifteen years of cyclone events on *per capita* GDP growth for the sample of developing countries excluding SIDS.
Notes: Developing countries are defined as in the World Economic Outlook reports, 2000 (International Monetary Fund). Estimations with outlier-robust regression. Standard errors are computed using the Street & al. (1988) correction. Shaded areas represent the associated 90 % confidence intervals.

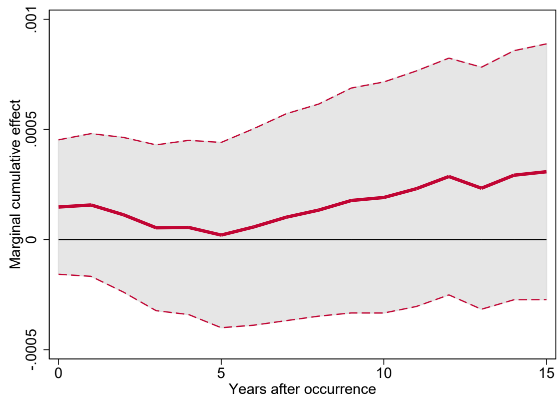

Figure D.2.3: Measures of the marginal cumulative effects over fifteen years of cyclone events on *per capita* GDP growth for the sample of developing countries that are highly dependent on agricultural sector, excluding SIDS.

Notes: Strong dependence on agricultural sector is defined as having an above median share of agricultural production among overall production (*i.e.* > 14% of overall GDP). Estimations with outlier-robust regression. Standard errors are computed using the Street & al. (1988) correction. Shaded areas represent the associated 90 % confidence intervals.

E Additional robustness checks

Table E.2.1: Regression results using alternative lag structures and keeping the same number of observations as the main model (2494).

	SIDS (1)	Non SIDS (2)
Immediate effect, $L = 0$	-0.00016***	0.00002
	(0.00005)	(0.00012)
Marginal cumulative effect, $L = 1$	-0.00015***	0.00006
	(0.00005)	(0.00013)
Marginal cumulative effect, $L = 5$	-0.00020***	-0.00005
	(0.00007)	(0.00016)
Marginal cumulative effect, $L = 10$	-0.00019**	-0.00015
	(0.00008)	(0.00019)

Notes: Estimations with outlier-robust regression. Standard errors incorporating the Street & al. (1988) correction are in parentheses. Time and country fixed effects, as well as temperature and precipitation controls (same number of lags as the cyclone indicator) are included in all specifications. This restriction implies that the sample period is limited to 1985-2015.
Significance levels : *** 1 % ; ** 5 % ; * 10 %.

Table E.2.2: Regression results using a sample that excludes countries affected by extratropical cyclones only.

	SIDS (1)	Non SIDS (2)
Immediate effect, $L = 0$	-0.00016***	0.00012
	(0.00004)	(0.00012)
Marginal cumulative effect, $L = 1$	-0.00015***	0.00016
	(0.00005)	(0.00013)
Marginal cumulative effect, $L = 5$	-0.00021***	0.00007
	(0.00007)	(0.00013)
Marginal cumulative effect, $L = 10$	-0.00023***	0.00001
	(0.00009)	(0.00019)
Marginal cumulative effect, $L = 15$	-0.00026**	-0.00027
	(0.00011)	(0.00025)

Notes: Estimations with outlier-robust regression. Standard errors incorporating the Street & al. (1988) correction are in parentheses. Time and country fixed effects, as well as temperature and precipitation controls are included in all specifications. This restriction excludes Algeria, Canada, France, Iceland, Ireland, Morocco, Norway, Portugal, Russia, Spain, and United Kingdom.
Significance levels : *** 1 % ; ** 5 % ; * 10 %.

Table E.2.3: Interaction of impacts between cyclone intensity and cyclone frequency.

	SIDS (1)	Non SIDS (2)
$\overline{Cyc}_{i,t} \times Nb.\ Cyc_{i,t}$		
Immediate effect, $L = 0$	-0.00008***	-3.29e-06
	(0.00005)	(0.00002)
Marginal cumulative effect, $L = 1$	-0.00006***	-4.38e-06
	(0.00002)	(0.00002)
Marginal cumulative effect, $L = 5$	-0.00009***	-0.00003
	(0.00003)	(0.00003)
Marginal cumulative effect, $L = 10$	-0.00012***	-0.00005*
	(0.00004)	(0.00002)
Marginal cumulative effect, $L = 15$	-0.00017***	-0.00008**
	(0.00005)	(0.00004)

Notes: Estimations with outlier-robust regression. Standard errors incorporating the Street & al. (1988) correction are in parentheses. Time and country fixed effects, as well as temperature and precipitation controls are included in all specifications.
Significance levels : *** 1 % ; ** 5 % ; * 10 %.

Table E.2.4: Immediate effect results using difference in differences estimator robust to heterogeneous treatment effects.

	SIDS (1)	Non SIDS (2)
DID_M	-0.00007**	-0.00015
	(0.00003)	(0.00010)
Observations	3676	3676

Notes: Estimations with De Chaisemartin & D'Haultfœuille (2020) difference in differences estimator robust to heterogeneous treatment effects across countries. Standard errors are clustered by country. 200 bootstrap replications.
Significance levels : *** 1 % ; ** 5 % ; * 10 %.

Table E.2.5: Regression results with a sample restricted to small countries only

	SIDS (1)	Non SIDS (2)
$\overline{Cyc}_{i,t}$		
Immediate effect, $L = 0$	-0.00017***	0.00005
	(0.00005)	(0.00013)
Marginal cumulative effect, $L = 1$	-0.00014***	0.00008
	(0.00005)	(0.00014)
Marginal cumulative effect, $L = 5$	-0.00022***	0.00002
	(0.00007)	(0.00019)
Marginal cumulative effect, $L = 10$	-0.00023***	-0.00005
	(0.00009)	(0.00021)
Marginal cumulative effect, $L = 15$	-0.00024**	-0.00023
	(0.00012)	(0.00028)

Notes: Estimations with outlier-robust regression. Standard errors incorporating the Street & al. (1988) correction are in parentheses. Time and country fixed effects, as well as temperature and precipitation controls are included in all specifications.
Significance levels : *** 1 % ; ** 5 % ; * 10 %.

Table E.2.6: Regression results using a binary variable of cyclone occurrence in SIDS

$\mathbb{1}_{\{\overline{Cyc}_{i,t}>0\}}$	
Immediate effect, $L = 0$	-0.00551***
	(0.00208)
Marginal cumulative effect, $L = 1$	-0.00450
	(0.00284)
Marginal cumulative effect, $L = 5$	-0.00682
	(0.00504)
Marginal cumulative effect, $L = 10$	-0.00032
	(0.00758)
Marginal cumulative effect, $L = 15$	-0.00559
	(0.01059)

Notes: Estimations with outlier-robust regression. Standard errors incorporating the Street & al. (1988) correction are in parentheses. Time and country fixed effects, as well as temperature and precipitation controls are included in all specifications.
Significance levels : *** 1 % ; ** 5 % ; * 10 %.

Table E.2.7: Regression results, using a quadratic model.

$\overline{Cyc}_{i,t}$	0.00021
	(0.00026)
$\overline{Cyc}^2_{i,t}$	-2.03e-06
	(5.23e-06)
$\overline{Cyc}_{i,t} \times SIDS$	-0.00033
	(0.00028)
$\overline{Cyc}^2_{i,t} \times SIDS$	1.60e-06
	(5.33e-06)
Observations	3676
Adjusted R^2	0.25
Contemporaneous effect in SIDS ($\overline{Cyc}_{i,t}$)	-0.00012
	(0.00010)
Contemporaneous quadratic effect in SIDS ($\overline{Cyc}^2_{i,t}$)	-4.30e-07
	(1.03e-06)

Notes: Outlier-robust regression estimates. Standard errors incorporating the Street & al. (1988) correction are in parentheses. Time and country fixed effects, as well as temperature and precipitation controls are included, but not reported in the table.
Significance levels : *** 1 % ; ** 5 % ; * 10 %.

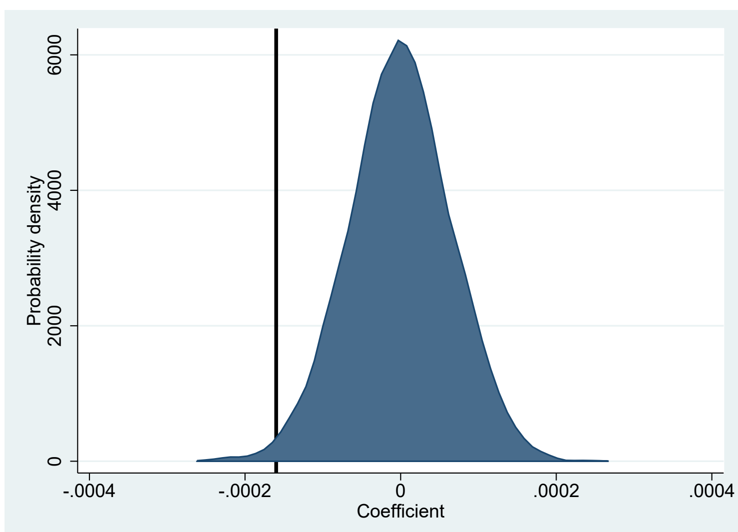

Figure E.2.1: Distribution of tropical cyclone contemporaneous variable's point estimates determined by re-estimating the equation of interest (equation (2.3), $L = 0$) with randomized placebo datasets. Randomized datasets consist in within country randomization, *i.e.* reassigning the timing of cyclone events for each country. Randomization and estimation procedures with 10,000 iterations. $N = 3676$. The coefficient obtained when using real data is displayed as vertical lines (-0.00016, with p-value < 0.01).

F Channels: additional estimations

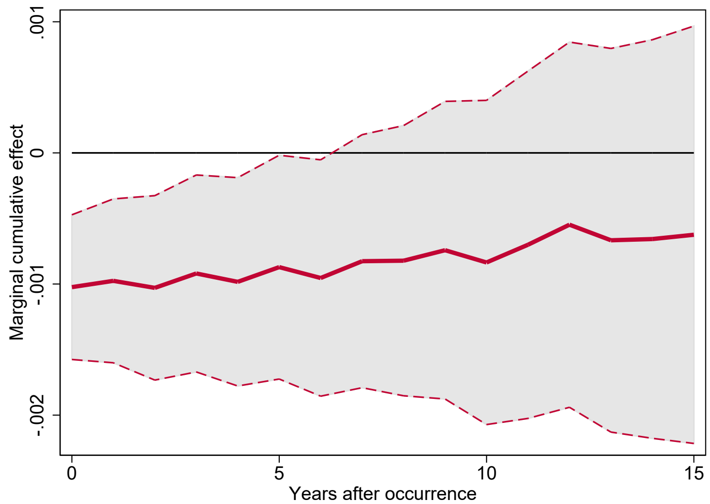

Figure F.2.1: Measures of the marginal cumulative effects over fifteen years of cyclone events on tourism receipts growth (measured in constant 2015 US$) for small island developing states.
Notes: N=1270. Data on tourism receipts come from the *World Development Indicators* database of the World Bank. Estimations with outlier-robust regression. Standard errors are computed using the Street & al. (1988) correction. Shaded areas represent the associated 90 % confidence intervals.

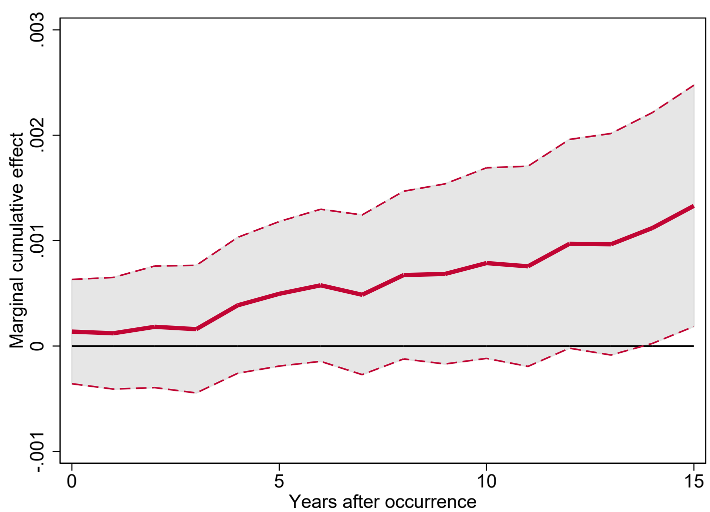

Figure F.2.2: Measures of the marginal cumulative effects over fifteen years of cyclone events on remittances growth (measured in constant 2015 US$) for small island developing states.
Notes: N=2062. Data on remittances come from the *World Development Indicators* database of the World Bank. Estimations with outlier-robust regression. Standard errors are computed using the Street & al. (1988) correction. Shaded areas represent the associated 90 % confidence intervals.

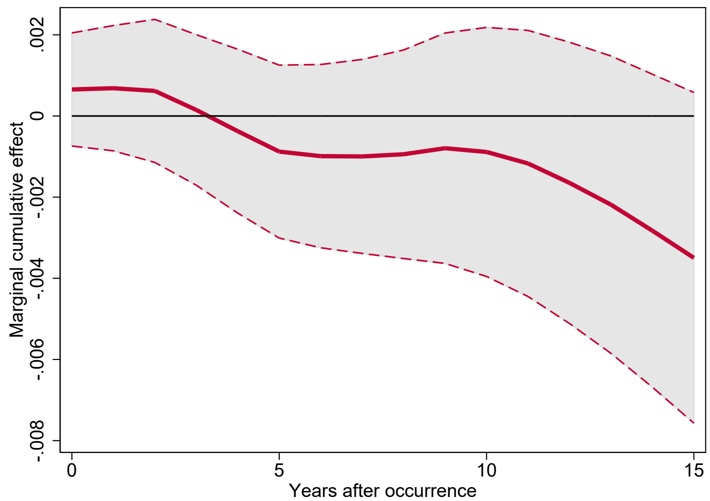

Figure F.2.3: Measures of the marginal cumulative effects over fifteen years of cyclone events on the logarithm of debt-to-GDP ratio for small island developing states.
Notes: N=701. Data on debt-to-GDP ratio come from the *World Development Indicators* database of the World Bank. Estimations with outlier-robust regression. Standard errors are computed using the Street & al. (1988) correction. Shaded areas represent the associated 90 % confidence intervals.

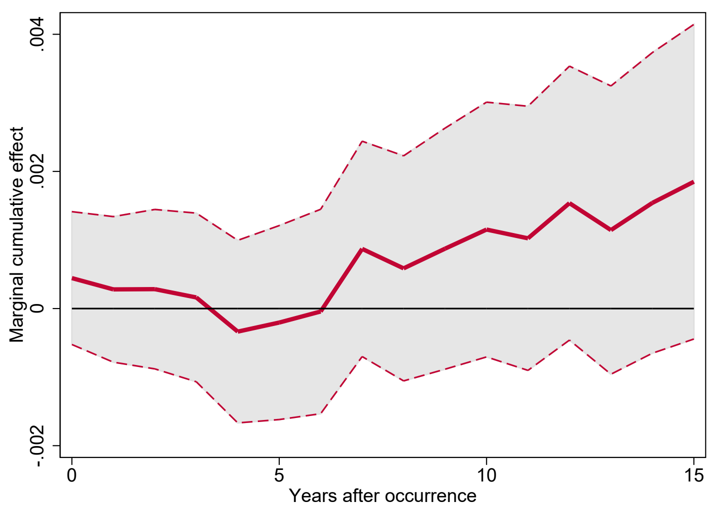

Figure F.2.4: Measures of the marginal cumulative effects over fifteen years of cyclone events on net official development assistance and official aid growth for small island developing states.
Notes: N=1929. Data on development assistance and aid come from the *World Development Indicators* database of the World Bank. Estimations with outlier-robust regression. Standard errors are computed using the Street & al. (1988) correction. Shaded areas represent the associated 90 % confidence intervals.

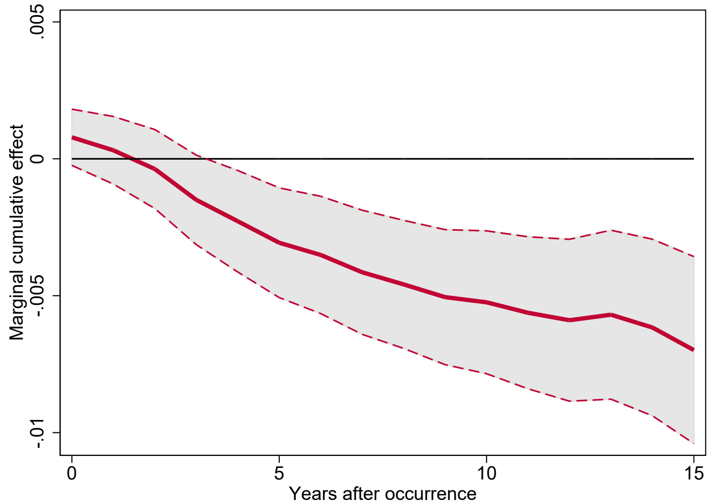

Figure F.2.5: Measures of the marginal cumulative effects over fifteen years of cyclone events on the logarithm of private investment-to-GDP ratio for small island developing states.
Notes: N=899. Data on private investment-to-GDP ratio come from the *World Development Indicators* database of the World Bank. Estimations with outlier-robust regression. Standard errors are computed using the Street & al. (1988) correction. Shaded areas represent the associated 90 % confidence intervals.

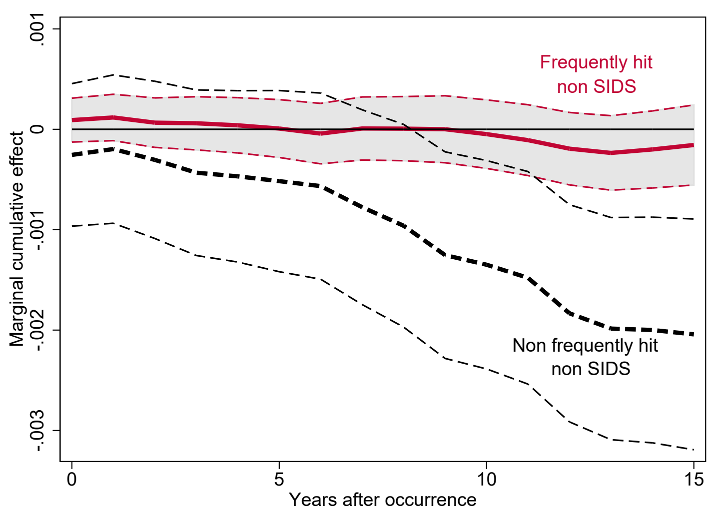

Figure F.2.6: Measures of the marginal cumulative effects over fifteen years of cyclone events on *per capita* GDP growth for frequently hit countries excluding small island developing states.
Notes: Estimations with outlier-robust regression. Standard errors are computed using the Street & al. (1988) correction. Shaded areas represent the associated 90 % confidence intervals obtained for frequently hit states. Black dashed lines correspond to the estimations for the complementary subgroup of non frequently hit countries excluding small island developing states (SIDS).

Chapter 3

The growth effects of tropical cyclones in a non small island developing state: the U.S.' case study

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Abstract

Tropical cyclones have always been a concern for public authorities in the U.S., with a season lasting nearly half of the year. Using longitudinal data on economic growth and exposure to tropical cyclones, we provide new comprehensive analyses of these disasters' growth impact in U.S. states and counties. While we find that results remain insignificant with country-wide samples, this study shows that the effects can be, instead, significant at regional level. In fact, a specific analysis of Florida State stresses significant short-term negative effects, both at county and state levels. At this stage, this study calls for an in-depth investigation of the underlying mechanisms leading to such growth depletion but already pins down the important heterogeneity in the effects of a catastrophe on growth patterns within a country.

Keywords: Natural disasters; Cyclones; Growth; Economic impacts; Environmental issues
JEL classification: O44; Q54; R11

1 Introduction

Natural disasters commonly designate catastrophic events caused by natural processes of the Earth. These phenomena are often distinguished between those of geological, climatic or even biological nature. Throughout history, their consequences on human systems and societies have always been felt, and the ability to predict or prepare for them has accordingly represented a perennial challenge. In the context of assessing the impacts of natural disasters, the U.S. turns out to be an interesting case study as it is exposed to a wide range of disasters such as volcanic eruptions, earthquakes, winter storms, tornadoes, wildfires, droughts etc. This paper particularly focuses on tropical cyclones, which are arguably the costliest and the most threatening for material assets.

Among other countries, the U.S. regularly vied for the attention of researchers in the empirical literature. Some single-event studies such as those on the 2005 Hurricane Katrina examine the impact on jobs or population displacement, housing market, education or health outcomes (Vidgor, 2008; Groen & Polivka, 2008; Sacerdote, 2012; Deryugina & al., 2018; Deryugina & Molitor, 2020). More closely related to the present study, Strobl (2011) evaluates the impact of hurricanes on U.S. coastal areas' economic growth from 1970 to 2005. On the year the hurricane occurs, a detrimental effect is estimated at county level, while this negative impact is only detected on the quarter of occurrence and is offset by the end of the year at state level. Finally, no significant effect is perceived at national level.

Using annual and quarterly panel data sets of U.S. counties' or states' economic growth respectively from 1970 to 2020, this paper provides a reappraisal of the latter research question in the context of tropical cyclones for different levels of exposure. To achieve this, we exploit a geophysical data set to build a physical intensity measurement for all tropical cyclones that affect the U.S. at some point in their trajectory. Then, as tropical cyclones not only affect directly impacted areas but also neighboring territories, we resort to spatial panel models as in Strobl (2011) to take into consideration the influence of contiguous counties' or states' growth on each area under study. Overall, across our different panels of states or counties, we find that tropical cyclones do not disrupt economic activity. These results perhaps differ from those in Strobl (2011) as we use a slightly different sample of U.S. counties or exploit a 15-year longer panel. Probably more importantly, this difference in results might stem from our cyclone intensity measurement, which is different than the one he uses. In a second phase of the study, we focus on one particular state, namely Florida. The interest in this State is not new in the empirical literature. Belasen & Polachek (2009) stress the negative impact on local employment in the wake of hurricanes. This detrimental effect leads, in counterpart, to a positive relationship between hurricane occurrence and earnings in the short-run. Brown & al. (2021) evaluate revenue losses within the tourism sector due to tropical cyclones and highlight the increased effect on waterfront counties compared to those located deeper in Floridian lands. More recently, Pollack & Kaufmann (2022) demonstrate how cyclonic risk is imperfectly captured in Florida Keys' housing prices. Unlike other states in the U.S., Florida combines several characteristics that might amplify tropical cyclones' impacts. First, it is the most frequently exposed state in the U.S., while it is one of the richest states and one of the most populated. The latter combination of factors is even more concerning than Florida's largest metropolitan areas such as Miami are all located close to the shoreline where tropical cyclones make landfall with the greatest intensity. Finally, as pointed out in the above literature review, Florida has an increased vulnerability due to the importance of tourism for its economy. This single-state assessment is carried out by means of time series analysis which constitutes one of the novelties in this paper. After having a built stationary measurement for quarterly economic growth, our modeling concludes with a continuous negative effect over a year, but which is merely significant on the quarter the cyclone occurs and two quarters later. These conclusions at state level are emphasised by complementary results on Floridian counties, which suggest that growth penalties accumulate over three years on a smaller scale. At last, the main contributions of this paper originate from its complete replicability, the use of updated data up to 2020, a twofold econometric strategy and a specific focus on Florida.

The paper is structured as follows. Section 2 introduces the cyclone and economic data, and describes construction of a stationary measure of economic growth at state level. Section 3 presents the methodology as well as the main results on the effects of tropical cyclones on U.S. economic growth at different geographical levels while Section 4 examines the specific case of Florida. Finally, Section 5 concludes.

2 Data

This section introduces the data. First, we present those exploited in order to build our tropical cyclone intensity measurement. Then, the set of economic data at the state and county levels is presented. As the analysis of personal income per capita data at state level discloses the existence of seasonality, all the transformations made to address this issue are described step-by-step.

2.1 Cyclone data

Our primary cyclone data come from from Tropical Cyclone Exposure Database (TCE-DAT; Geiger & al., 2018), with an extension up to 2020 kindly provided by the research team upon request. TCE-DAT is a longitudinal data set on each landfalling tropical cyclone event worldwide from 1950 to 2020. As this paper focuses on the U.S., we only extract data related to this country, *i.e.* the events that have affected the U.S. at some point of their trajectory. TCE-DAT reports wind speed and location data for each cyclone event that has reached at least 34 knots ($\approx$ 63 km/h) wind speed for at least one minute. It actually relies on the set of events reported by the widely used International Best Track Archive for Climate Stewardship (IBTrACS; Knapp & al., 2010), maintained by the National Climatic Data Center of the National Oceanic and Atmospheric Administration (NOAA). Using the 6-hourly observations on latitude and longitude position, wind speed, surface air pressure and trajectory of cyclone centres (called the "eye") provided by the IBTrACS, TCE-DAT builds overall cyclone trajectories and intensities at 0.1° latitude x 0.1° longitude grid cell level for each of the aforementioned event by applying Holland's (2008) wind field model. Hence, we consider here all the events during which at least one grid cell of the U.S. is hit according to the simulated wind field. Due to economic data limitations, our panel starts in 1970 and ends in 2020. Florida is the most frequently hit State during this time period with 83 events recorded, followed by North Carolina, Louisiana and Texas, with respectively 65, 54 and 53 cyclone events (Figure 3.1).

Apart from being the most exposed State in the U.S., Florida is also characterized by a wide range of factors of vulnerability regarding cyclonic risk. These factors are detailed, in-depth, in section 4 and constitute the reason why we choose to focus on this specific state in a second part of the study. Among others, the exposure to cyclonic risk is homogeneous in Florida, as it is shown in Figure 3.2. The yearly average wind speed over Florida calculated from 1970 to 2020 shows small dispersion as this State is often entirely affected when it is hit by a tropical cyclone, unlike Texas, for instance, where all areas are not exposed to cyclonic risk.

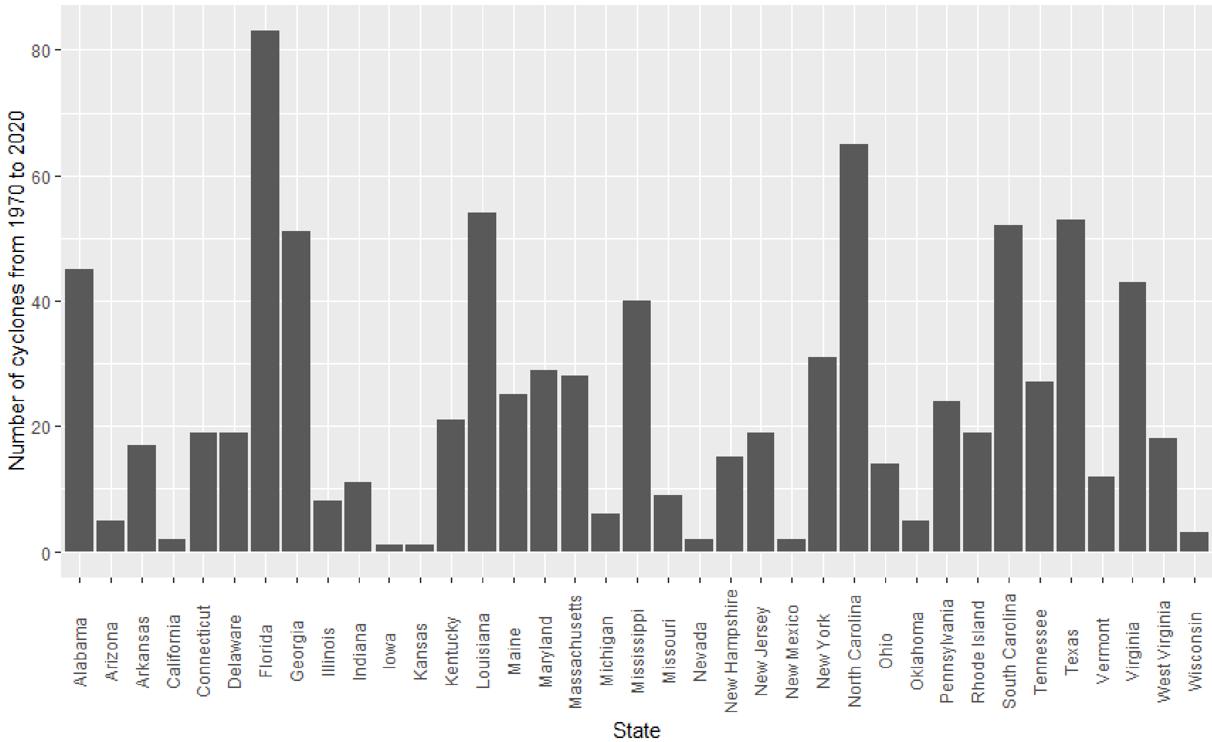

Figure 3.1: Total number of cyclone events from 1970 to 2020 in the contiguous U.S., by state.

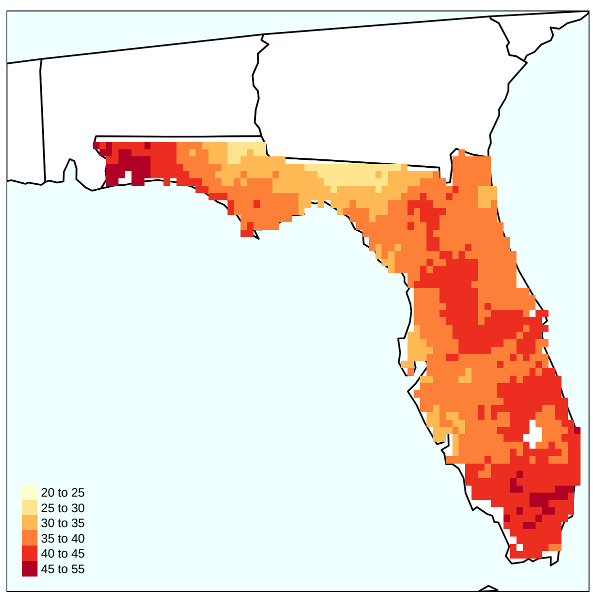

Figure 3.2: Yearly average wind speed (in km/h) at pixel level in Florida from 1970 to 2020.

2.2 Economic data

Data on personal income are taken from the Bureau of Economic Analysis's (BEA) regional economic accounts. More specifically, we extract data on Quarterly Personal Income by State as well as Local Area Personal per Capita Income, which provides annual county-level estimates from 1969 to 2020. The BEA defines personal income as the income received by people from labor, properties, financial income such as interests or dividends, rents, and government benefits. As personal income data are released in current US$ values, these have been converted to constant 2020 US$ using the consumer price index reported by the U.S. Bureau of Labor Statistics. State level personal income per capita data are obtained after including state population data from the U.S. Bureau Census (2021) to our data set. The advantages of using this specific variable to describe economic growth are twofold. Firstly, using personal income per capita data let us remain in line with Strobl (2011). Then, unlike data on gross domestic product reported by the BEA, these are available with a quarterly frequency, which brings an enhancement compared to chapter 2 and offers the possibility to examine the time path of the effect with more accuracy.

Having said that, as we are in the context of panel data, it is necessary to assess whether these personal income per capita series are stationary. To do this, we first run panel and individual unit root tests for each series (logged) in levels and in first-difference for State level quarterly personal income per capita data. Table 3.1 outlines the results. According to the individual unit root tests, *i.e.* the Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) test, and one of the panel unit root tests, *i.e.* the Im-Pesaran-Shin (IPS) test, first differencing the series seems to remove the unit root. However, the Levin-Lin-Chu (LLC) panel unit root test suggests that there is a problem as the null hypothesis of having at least one non stationary series among the panel is accepted with a P-value of 1.

Table 3.1: Unit root rests for raw series

Individual unit root tests	Fraction of states for which test is rejected at the 10% level	*Panel unit root tests*	P-value of the test
1) Personal income per capita (logged) in levels		1) Personal income per capita (logged) in levels	
Augmented Dickey-Fuller test	0/37	*Levin-Lin-Chu test*	0.4705
Philips-Perron test	2/37	*Im–Pesaran–Shin test*	1.0000
2) Personal income per capita (logged) in first-difference		2) Personal income per capita (logged) in first-difference	
Augmented Dickey-Fuller test	37/37	*Levin-Lin-Chu test*	**1.0000**
Philips-Perron test	37/37	*Im–Pesaran–Shin test*	0.0000

Notes: Augmented Dickey-Fuller tests with 5 lags and trend. Philips-Perron tests with 5 lags and trend. Levin-Lin-Chu tests with 3 lags and trend, H_0 = panels contain unit roots
Im–Pesaran–Shin tests with 3 lags and trend, H_0 = all panels contain unit roots

To deal with this issue, we compute the auto-correlation function (ACF) of one of our series and analyse the results. Figure 3.3 plots the ACF obtained for Florida, and the latter highlights the presence of seasonality, which explains the results presented in Table 3.1.

Finally, to remove the seasonality in the data, we use the X-13-ARIMA-SEATS program developed jointly by the U.S. Census Bureau and the Bank of Spain. The result of this seasonal adjustment program is shown in Figure 3.4 in the case of Florida, and Table 3.2 now shows that first-differences of deseasonalized series are all stationary.

Regarding our cyclone data, it is found to be $I(0)$ across all unit root tests in levels, and further examination of its ACF shows that this series is arguably exogenous. As for county level annual personal income per capita, first differencing the series is enough to render them stationary.[1]

[1]All the statistical tests related to both of these variables are available upon request.

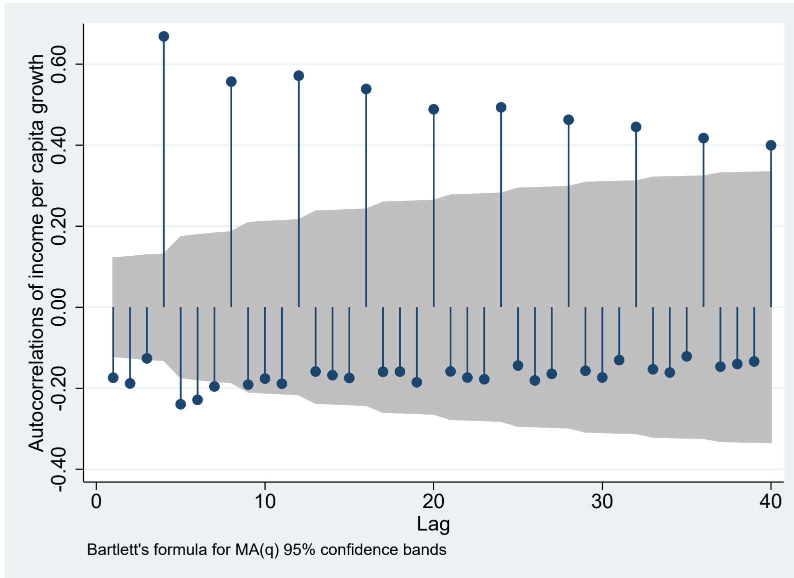

Figure 3.3: ACF for Floridian quarterly personal income per capita growth rate

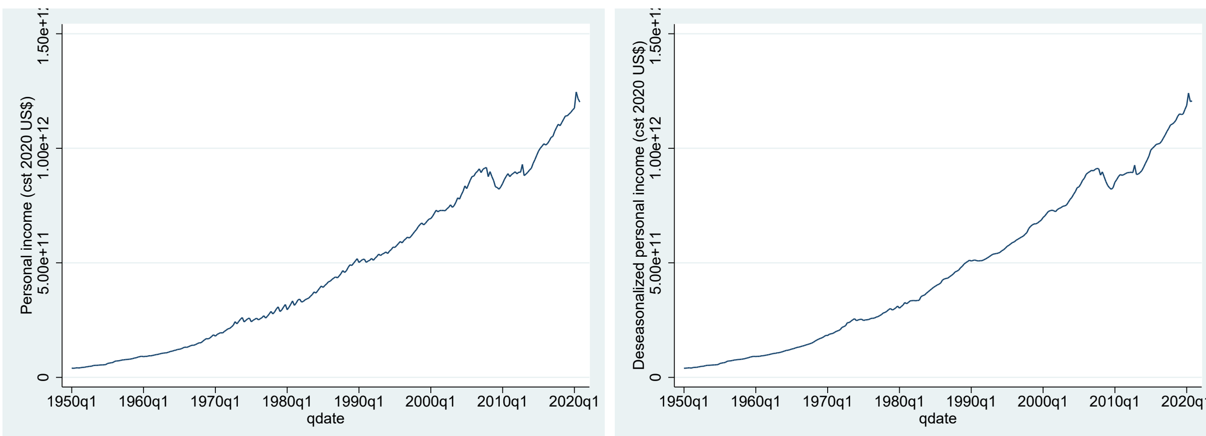

Figure 3.4: Plots for Floridian quarterly personal income through time. Deseasonalized series on right hand-side.

Table 3.2: Unit root rests for deseasonalized series

Individual unit root tests	Fraction of states for which test is rejected at the 10% level	*Panel unit root tests*	P-value of the test
1) Personal income per capita (logged) in levels		1) Personal income per capita (logged) in levels	
Augmented Dickey-Fuller test	0/37	*Levin-Lin-Chu test*	0.0001
Philips-Perron test	0/37	*Im–Pesaran–Shin test*	0.9972
2) Personal income per capita (logged) in first-difference		2) Personal income per capita (logged) in first-difference	
Augmented Dickey-Fuller test	37/37	*Levin-Lin-Chu test*	**0.0000**
Philips-Perron test	37/37	*Im–Pesaran–Shin test*	0.0000

Notes: Augmented Dickey-Fuller tests with 5 lags and trend. Philips-Perron tests with 5 lags and trend.
Levin-Lin-Chu tests with 3 lags and trend, H_0 = panels contain unit roots
Im–Pesaran–Shin tests with 3 lags and trend, H_0 = all panels contain unit roots

3 Measuring the impact of tropical cyclones on economic growth from state to county level

This third section outlines our methodology and main results. After having described the construction of our cyclone intensity predictor, this section presents the econometric model selected to measure the impact of tropical cyclones on economic activity and the obtained results. In a last subsection, we check the robustness of our main results for a variety of changes in the empirical framework.

3.1 Cyclone intensity measurement

This paper relies on a physical measure of tropical cyclones that is measured quarterly to fit with our state level economic data time interval, and annually for our analyses at county level. It takes the form of a population-weighted average of the maximum sustained wind speed over all pixels in each state - respectively, county - in a given sample. Mathematically, one can write the indicator at state level as:

$$\overline{Cyc}_{i,q} = \frac{\sum_{p=1}^{P_i} \max_{s \in \{1,\ldots,S_{p,i,q}\}} \{Wind_{p,s,i,q}\} Exposed\ Population_{p,q}}{Total\ Population_{i,q}} \tag{3.1}$$

where $Wind_{p,s,i,q}$ is the wind speed recorded in pixel p, for storm s that struck state i in quarter q. $Exposed\ Population_{p,q}$ corresponds to the estimated population in pixel p and reported in TCE-DAT, while $Total\ Population_{i,q}$ is the number of inhabitants in state i during quarter q as estimated in the U.S. Bureau Census (2021) data set. All pixel values are then averaged across the total number of pixels per state P_i.

As for the yearly indicator, it includes a temporal weight $(12 - m_{p,s})/12$ as in Noy (2009), this additional parameter is incorporated to capture the contemporaneous impact with more accuracy as a cyclone that strikes in the early months of a given year has arguably a bigger impact in the same year than another one - with same intensity - occurring some months later. This augmented version of equation (3.1) can be written as follows:

$$\overline{Cyc}_{c,t} = \frac{\sum_{p=1}^{P_c} \max_{s \in \{1,\ldots,S_{p,c,t}\}} \{Wind_{p,s,c,t}\} \left(\frac{12 - m_{p,s}}{12}\right) Exposed\ Population_{p,t}}{Total\ Population_{c,t}} \tag{3.2}$$

with $m_{p,s}$ the month in which the storm occurred, and with county and year indices corresponding respectively to c and t. This monthly weighting is a core characteristic in our model as tropical cyclone season in the U.S. runs from June to November.

Whether the indicator is measured at state or county level, we select the maximum wind speed value felt in each pixel each period, irrespective of the number of cyclone events S identified within each pixel for the given year as in Felbermayr & Gröschl (2014). This methodological choice is challenged in robustness estimations with an analysis of the impact with respect to the frequency of events.

In each case, the indicator weights wind speed levels over all pixels by the share of exposed population. Such weighting process follows recommendations to normalize natural disaster predictors in Nordhaus (2006). Ultimately, the aim is to determine the average effect of storm events on an average pixel for a given area. This measurement can also be interpreted as an estimate of a cyclone's average intensity in a randomly selected unit of land for each county, or the value of a given cyclone's intensity if this one had struck the county homogeneously across all its locations (Hsiang & Jina, 2014).

3.2 Empirical strategy

The empirical framework follows essentially Strobl (2011) and resort to analyses with spatial panel models including a lagged value for the log of personal income per capita, so that spatial correlations between states - or likewise, counties - and initial growth conditions are properly considered. More specifically, among the wide range of spatial dependence models, our specification tests for states, which are presented in Appendix A, call for the use of spatial error model (SEM), which can be expressed as follows:

$$g_{i,q} = \alpha ln(Pers.Inc.pc)_{i,q-1} + \beta\overline{Cyc}_{i,q} + \mu_i + \delta_q + u_{i,q} \tag{3.3}$$
$$u_{i,q} = \lambda \sum_{i \neq j} w_{i,j} u_{j,q} + \varepsilon_{i,q}$$

with, $g_{i,q} = ln(Pers.Inc.pc)_{i,q} - ln(Pers.Inc.pc)_{i,q-1}$ for a state i and quarter q. $w_{i,j}$ corresponds to an element of the spatial weighting matrix $W_N \in \mathbb{R}^{N\times N}$, which defines neighboring relationships between each of the N states. Here, W_N is a stochastic matrix. Each of its rows represents a State, and a value strictly greater than zero and lower than one is assigned to all the territories that are contiguous to this State. Contiguity is defined by the queen criterion - as opposed to the rook or the bishop criterion -, meaning that all the territories that have common borders have a non-zero value. This value corresponds to the share of common borders the territory has with the considered State. Accordingly, if a State has only one contiguous territory, then the latter would be attributed the value 1, and all other States would have zero. μ_i and δ_q represent respectively unobserved state-specific and time-specific effects. λ denotes the scalar spatial autoregressive coefficient, and assumed to verify $|\lambda| < 1$. Finally, we assume that $\varepsilon_{i,q}$ are all independent and identically distributed with mean 0 and finite variance σ^2_ε.

As for county level estimations, specification tests leading to the choice of a SEM are rejected. Instead, results rather show that the appropriate model corresponds to a spatial autoregressive model with autoregressive disturbances (SARAR), also called spatial autocorrelated model (SAC) which is a more general class of spatial models than SEM.[2] Thus, the equation of interest for counties corresponds to:

$$g_{c,t} = \rho \sum_{c \neq j} w_{c,j} g_{j,t} + \alpha ln(Pers.Inc.pc)_{c,t-1} + \beta\overline{Cyc}_{c,t} + \mu_c + \delta_t + u_{c,t} \tag{3.4}$$

$$u_{c,t} = \lambda \sum_{c \neq j} w_{c,j} u_{j,t} + \varepsilon_{c,t}$$

where indices c and t are related to a given county and year, respectively. The dependent variable, all regressors and disturbances are defined as in the previous equation, with the exception that, now, the equation of interest includes a spatial lag $Wg = \sum_{c \neq j} w_{c,j} g_{j,t}$, and as λ its regression coefficient is also assumed to be bounded in absolute value: $|\rho| < 1$.

[2]See Baltagi (2021) for a detailed presentation of spatial panel models.

As already stated in subsection 3.1, the availability of quarterly data at state level allows for greater accuracy in the impact evaluation. More importantly, the latter point also offers the possibility to withdraw the monthly weighing that is included to $\overline{Cyc}_{c,t}$ in county-year analyses.

In what follows, we split up our sample into three categories for states, and five categories for counties. First, we consider all 48 contiguous U.S. states (respectively all counties). Then we run regressions on the subsample of exposed states (respectively exposed counties). Third, we focus on 19 coastal states as in Strobl (2011) and all their counties that are exposed to tropical cyclones. In addition, we estimate the impact of tropical cyclones on coastal counties and on shoreline counties as defined by the NOAA. NOAA's list of coastal counties is based on NOAA coastal watersheds and U.S. Geological Survey's (USGS) coastal cataloging units. It corresponds to counties within which water flows into the ocean or Great Lakes. A coastal watershed county has at least 15 percent of its area in a coastal watershed or has a land area that accounts for at least 15 percent of a coastal cataloging unit as defined by the USGS. Shoreline counties are a subgroup of coastal counties. These counties are defined as those that are directly adjacent to the open ocean, major estuaries, and the Great Lakes.[3] Both of these categories are highlighted in Figure 3.5. Table 3.3 summarizes economic growth and cyclone intensity measurement data for each different sample. At state level, the highest cyclone measurement value is recorded in New Jersey in 2012 (Q4) when the State was affected by Hurricane Sandy (178.8 km/h). As for counties, according to our indicator, the most powerful cyclonic year is recorded in Baker County in Georgia in 2018 (196.2 km/h), followed by Cameron County in Louisiana in 2005 (186.4 km/h).

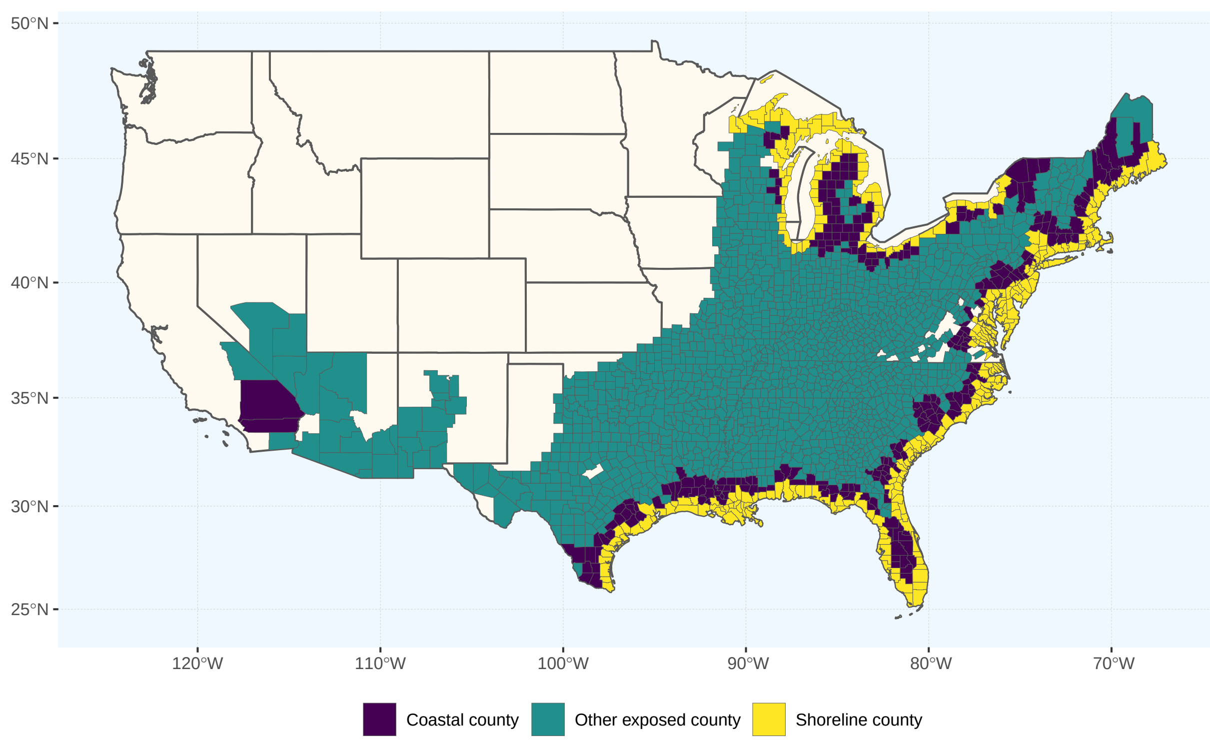

Figure 3.5: Categories of counties that were exposed to tropical cyclones from 1970 to 2020, given their geographical position in the U.S. and based on NOAA classification.

[3]For further information on these definitions, see `https://coast.noaa.gov/digitalcoast/training/defining-coastal-counties.html`.

Table 3.3: Summary Statistics

	Sample	Obs.	Average values from 1970 to 2020 Mean	Std. Dev.	Min.	Max.
State level variables						
Personal income per capita growth rate ($g_{i,q}$)	All states	9792	0.0038	0.017	-0.25	0.19
	Exposed states	7548	0.0037	0.014	-0.11	0.15
	Coastal states	3876	0.0039	0.013	-0.081	0.11
Cyclone intensity measurement ($\overline{Cyc}_{i,q}$)	All states	9792	2.59	13.7	0	171.8
	Exposed states	7548	3.35	15.5	0	171.8
	Coastal states	3876	5.51	19.9	0	171.8
County level variables						
Personal income per capita growth rate ($g_{c,t}$)	All counties	154938	0.016	0.066	-1.36	1.47
	Exposed counties	104652	0.016	0.045	-1.24	1.33
	Coastal states' counties	55335	0.017	0.048	-1.24	1.33
	NOAA coastal counties	21573	0.017	0.042	-1.24	1.06
	NOAA shoreline counties	11832	0.017	0.044	-1.24	1.06
Cyclone intensity measurement ($\overline{Cyc}_{c,t}$)	All counties	154938	3.02	12.4	0	196.2
	Exposed counties	104652	4.47	14.9	0	196.2
	Coastal states' counties	55335	6.58	18.0	0	196.2
	NOAA coastal counties	21573	9.91	21.7	0	186.4
	NOAA shoreline counties	11832	11.4	23.7	0	186.4

3.3 Results at state level

Table 3.4 outlines the results at state level. Across all our estimations on different samples, results remain statistically insignificant. Notwithstanding the absence of impact of tropical cyclones on states' economic growth with almost zero point estimates across all our estimations, these results confirm the presence of spatial autocorrelation within our data set as the spatial error coefficient λ is always significant at the 1% level. This confirms that ignoring spatial correlation in the error term would have underestimated standard errors, which, in turn, would have potentially led to misleading inferences.

Additional estimations that include lagged values of cyclone predictor are presented in Appendix B. Indeed, one can rightly think that the impact of tropical cyclones might be visible only some quarters later. As such, we include up to three lags so that the impact is now estimated over a year. This change in specification does not alter the above conclusions, and the impact is consistently insignificant in the three quarters that follow the one when the cyclone makes landfall.

3.4 Results at county level

Table 3.5 presents the results from estimating equation (3.4), *i.e.* at county level. Once again, the null hypothesis that tropical cyclones do not affect growth is accepted across all our estimations. Columns 1 to 4 show a negative but statistically insignificant relationship between cyclone intensity and economic activity on average across all U.S. counties, exposed counties, coastal states' counties, or coastal counties as defined by the NOAA. In contrast, point estimate is positive and non-significant on average across our last sample of shoreline counties. As in our estimations at state level, results confirm the presence of spatial autocorrelation as coefficients on the spatially lagged dependent variable and spatial error term are both significant at the 1%

Table 3.4: Results for regressing quarterly state growth on cyclone intensity

	All states (1)	Exposed states (2)	Coastal states (3)
$ln(Pers.Inc.pc)_{i,q-1}$	-0.034***	-0.021***	-0.020***
	(0.003)	(0.002)	(0.003)
$\overline{Cyc}_{i,q}$	-8.54e-07	6.61e-06	0.00001
	(0.00001)	(7.63e-06)	(8.22e-06)
λ	0.40***	0.25***	0.17***
	(0.01)	(0.02)	(0.02)
Overall R^2	0.00	0.00	0.00
Observations	9792	7548	3876
Number of states	48	37	19

Notes: Spatial error model estimator with two-way fixed effects. Robust standard errors are in parentheses. Time and state fixed effects are included, but not reported in the table. Significance levels : *** 1% ; ** 5% ; * 10%.

level in all estimations, except for the sample of shoreline counties, where point estimate for ρ is significant at the 5% level. Additionally, to interpret the sign of the coefficient associated with ρ, as this one is negative, this means that neighboring counties have a detrimental effect on a given county's growth. Whether at county or at State level, our results are different than those in Strobl (2011). We argue that this inconsistency might arise from the use of a different cyclone measurement, a slightly different sample of coastal counties or our longer sample period.

Table 3.5: Results for regressing annual county growth on cyclone intensity

	All counties (1)	Exposed counties (2)	Coastal states' counties (3)	Coastal counties (NOAA definition) (4)	Shoreline counties (NOAA definition) (5)
$ln(Pers.Inc.pc)_{c,t-1}$	-0.182***	-0.130***	-0.137***	-0.108***	-0.122***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
$\overline{Cyc}_{c,t}$	-6.38e-06	-0.00001	-0.00001	-0.00002	5.48e-07
	(0.00001)	(0.00001)	(0.00002)	(0.00002)	(0.00002)
ρ	-0.093***	-0.073***	-0.066***	-0.084***	-0.025**
	(0.001)	(0.002)	(0.002)	(0.004)	(0.011)
λ	0.138***	0.127***	0.121***	0.131***	0.103***
	(0.0003)	(0.0007)	(0.0008)	(0.002)	(0.008)
Overall R^2	0.00	0.00	0.00	0.00	0.01
Observations	154938	104652	55335	21573	11832
Number of counties	3038	2052	1085	423	232

Notes: Spatial autocorrelated model estimator with two-way fixed effects. Robust standard errors are in parentheses. Time and county fixed effects are included, but not reported in the table. Significance levels : *** 1% ; ** 5% ; * 10%.

3.5 Robustness checks

This section considers a variety of robustness checks. Analyses are of two kinds. First, we keep the empirical strategy used above and consider robustness to alternative cyclone predictors. More specifically, on the one hand, we investigate an alternative formulation of our cyclone indicator that only keeps the share of exposed population as in Krichene & al. (2021). On the other hand, we check whether baseline results are altered when examining the effects of the frequency of cyclone events instead of our wind speed intensity measurement. Second, we reconsider the main specification and report the results when using a fixed effects estimator with Conley (1999) standard errors. These standard errors are robust to cross-sectional spatial dependence and serial correlation below some fixed cutoff values which are here set to 1000km and 3 time lags respectively. Hence, this alternative estimator provides a strong complement to our baseline spatial panel models estimations in which neighboring relationship is defined by sharing common borders. Results for each different state or county sample are summarized in Table 3.6 and Table 3.7.

State level

Overall, we find that using alternative indicators or changing the estimator does not change our conclusions. Removing the wind speed parameter from our baseline indicator does not change the sign of the relationship but increases the magnitude of coefficients. The quarterly number of cyclone events has a positive contemporaneous impact on average across all different samples, *i.e.* across all states, exposed states and coastal states. Finally, estimating equation (3.3) by applying a fixed effects estimator with Conley (1999) standard errors consistently displays negative immediate effects. However, in no case are these results statistically significant, meaning that state growth is arguably unaffected by tropical cyclone events in the quarter they occur.

County level

Table 3.7 reports the results for counties. Point estimates for the share of exposed population are positive across all estimations. The annual number of cyclone events has always a negative effect, except for the estimation on NOAA coastal counties. Estimations with Conley (1999) standard errors show a positive effect in the year the cyclone occurs across all samples. However, as none of the coefficients associated with our cyclone indicators are significant, the absence of impact is confirmed once again by these estimations.

4 Focusing on Florida

So far, our results show that tropical cyclones do not impact economic activity in the quarter they occur in U.S. states, but also in the year they occur in U.S. counties. Having said that, in a second phase, we wonder if our main results imply that there is no effect either if we address our research question at a smaller scale.

In particular, we now focus on Florida, which is the most frequently exposed state in the U.S. from 1970 to 2020 with 83 cyclones (Figure 3.1). This feature is all the more important, given that the following most frequently hit states are North Carolina with 65 events recorded during the sample period, then Louisiana with 54 tropical cyclones and Texas with 53. Hence, there is quite a large gap in the exposure to these catastrophes between Florida and its U.S. counterparts. Several other reasons might be put forward to justify a focus on this specific state when studying

Table 3.6: Robustness checks results: regressions on quarterly state growth

	All states (1)	Exposed states (2)	Coastal states (3)
Alternative cyclone indicator: share of exposed population			
$ln(Pers.Inc.pc)_{i,q-1}$	-0.034***	-0.021***	-0.020***
	(0.003)	(0.002)	(0.002)
$Pop.\ exposed_{i,q}$	-0.00004	0.0005	0.001
	(0.00100)	(0.0007)	(0.0008)
λ	0.40***	0.25***	0.17***
	(0.01)	(0.02)	(0.02)
Overall R^2	0.00	0.00	0.00
Observations	9792	7548	3876
Number of states	48	37	19
Alternative cyclone indicator: quarterly number of cyclone events			
$ln(Pers.Inc.pc)_{i,q-1}$	-0.034***	-0.021***	-0.020***
	(0.003)	(0.002)	(0.002)
$Nb.\ Cyc_{i,q}$	0.0002	0.0004	0.0003
	(0.0004)	(0.0003)	(0.0003)
λ	0.40***	0.25***	0.17***
	(0.01)	(0.02)	(0.02)
Overall R^2	0.00	0.00	0.00
Observations	9792	7548	3876
Number of states	48	37	19
Fixed effects estimator using Conley 1999 standard errors			
$ln(Pers.Inc.pc)_{i,q-1}$	0.0004***	0.0004***	0.0004***
	(0.00004)	(0.00004)	(0.00005)
$\overline{Cyc}_{i,q}$	-0.00002	-0.00002	-0.00002
	(0.00003)	(0.00003)	(0.00003)
R^2	0.05	0.07	0.08
Observations	9792	7548	3876
Number of states	48	37	19

Notes: The two first sections of the table report regressions that use spatial error model estimator with two-way fixed effects. Robust standard errors are in parentheses. Time and state fixed effects are included, but not reported in the table. Bottom section presents OLS regression results with standard errors corrected for cross-sectional spatial dependence and panel-specific serial correlation as in Conley (1999). The spatial correlation cutoff is 1000km, and the serial correlation one is 3 lags. Significance levels : *** 1% ; ** 5% ; * 10%.

cyclonic risk. Florida was the fourth richest state in the U.S. at the end of 2020, behind the States of New York, Texas and California according to our personal income data. It is also the third most populated State of the U.S. in 2020 behind Texas and California. In addition, one striking feature in Florida is the concentration of most of its largest metropolitan areas along the shoreline, or at least, considered as coastal according to the NOAA. Indeed, Miami, which is the 8th largest metropolitan area in the U.S. in 2020 with 6.1 million inhabitants, Tampa (18th largest), Orlando (22nd largest) and Jacksonville (39th largest) are all located near U.S. coasts, and arguably more likely to face higher cyclone intensities compared to other areas that would be located deeper in

Table 3.7: Robustness checks results: regressions on annual county growth

	All counties	Exposed counties	Coastal states' counties	Coastal counties (NOAA definition)	Shoreline counties (NOAA definition)
	(1)	(2)	(3)	(4)	(5)
Alternative cyclone indicator: share of exposed population					
$ln(Pers.Inc.pc)_{c,t-1}$	-0.182***	-0.130***	-0.136***	-0.108***	-0.122***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
$Pop.\ exposed_{c,t}$	0.0003	0.0001	0.0002	0.0002	0.0003
	(0.0003)	(0.0002)	(0.0003)	(0.0004)	(0.0005)
ρ	-0.093***	-0.073***	-0.066***	-0.083***	-0.025**
	(0.001)	(0.002)	(0.002)	(0.004)	(0.011)
λ	0.138***	0.127***	0.121***	0.131***	0.103***
	(0.0003)	(0.0007)	(0.001)	(0.002)	(0.008)
Overall R^2	0.00	0.00	0.00	0.00	0.01
Observations	154938	104652	55335	21573	11832
Number of counties	3038	2052	1085	423	232
Alternative cyclone indicator: yearly number of cyclone events					
$ln(Pers.Inc.pc)_{c,t-1}$	-0.182***	-0.130***	-0.136***	-0.108***	-0.122***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
$Nb.\ Cyc_{c,t}$	-0.0008	-0.0007	-0.0003	0.0003	-0.0002
	(0.0008)	(0.0006)	(0.0006)	(0.0008)	(0.0009)
ρ	-0.093***	-0.072***	-0.066***	-0.083***	-0.025**
	(0.001)	(0.0006)	(0.002)	(0.004)	(0.011)
λ	0.138***	0.127***	0.121***	0.131***	0.103***
	(0.0003)	(0.0007)	(0.001)	(0.002)	(0.008)
Overall R^2	0.02	0.00	0.00	0.00	0.01
Observations	154938	104652	55335	21573	11832
Number of counties	3038	2052	1085	423	232
Fixed effects estimator using Conley 1999 standard errors					
$ln(Pers.Inc.pc)_{c,t-1}$	0.002***	0.002***	0.002***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\overline{Cyc}_{c,t}$	0.00003	0.00003	0.00003	0.00005	0.00005
	(0.00005)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
R^2	0.05	0.11	0.11	0.14	0.13
Observations	154938	104652	55335	28203	15246
Number of counties	3038	2052	1085	423	232

Notes: The two first sections of the table report regressions that use spatial autocorrelated model estimator with two-way fixed effects. Robust standard errors are in parentheses. Time and county fixed effects are included, but not reported in the table. Bottom section presents OLS regression results with standard errors corrected for cross-sectional spatial dependence and panel-specific serial correlation as in Conley (1999). The spatial correlation cutoff is 1000km, and the serial correlation one is 3 lags. Significance levels : *** 1% ; ** 5% ; * 10%.

lands.[4] Notably, no other state exposed to tropical cyclones shows such geographic or demographic characteristics in our sample. Third, Florida's increased vulnerability to tropical cyclones due to this high concentration of population along the coasts is emphasised by a strong dependence on tourism activity. In fact, tourism represents the first source of revenue of the State. Agricultural activity, which is also at risk in the context of tropical cyclones, represented 1,2% of Floridian GDP in 2020 (United States Department of Agriculture, 2021). Hence, agriculture also brings a non-negligible contribution to Florida State's economy. Finally, as Florida is at the edge of the Caribbean, its local climate is more prone to higher cyclone exposure and intensities as it is surrounded by warmer water temperatures compared to other states due to its greater proximity to the equator. Florida also contains main harbours that export towards Latin America or the

[4] Population size rankings come from U.S. Census Bureau data. For further information, see `https://www.census.gov/data/tables/time-series/demo/popest/2020s-total-metro-and-micro-statistical-areas.html`.

Caribbean. For all these reasons, several studies on the economic impact of tropical cyclones have chosen to focus on Florida (Belasen & Polachek, 2009; Brown & al., 2021; Pollack & Kaufmann, 2022).

4.1 State level analysis

To estimate the impact of tropical cyclones on Floridian economic growth, we opt for an Auto-Regressive Integrated Moving Average with exogenous factors (ARIMAX) model and follow the Box & Jenkins (1976) time series modeling approach. This method consists in a three-stage procedure: model identification, parameter estimation, and diagnostic checking. In the present case, the equation of interest is expressed as:

$$g_t = A(L)g_{t-1} + B(L)\overline{Cyc}_t + C(L)\varepsilon_t \tag{3.5}$$

with $A(L), B(L)$ and $C(L)$ polynomials in the lag operator L, g (deseasonalized) personal income per capita growth, $\overline{Cyc}_t$ the usual population-weighted average of the maximum sustained wind speed over all pixels in Florida each quarter t, and ε the white noise error term, independent and identically distributed.

The identification step relies on an examination of the time path and the autocorrelation function (ACF) of Floridian series in order to get information about stationarity, structural breaks, trends, or seasonality. This step corresponds to the analyses presented at the end of section 2, and led to the choice of g_t. Floridian growth's ACF and PACF suggest that the model can be either autoregressive (AR) as point estimates are alternating positive and negative, or a mixed autoregressive and moving average (ARMA) model as the decay is starting after a couple of lags, and more specifically, here, five lags (Figure 3.6).

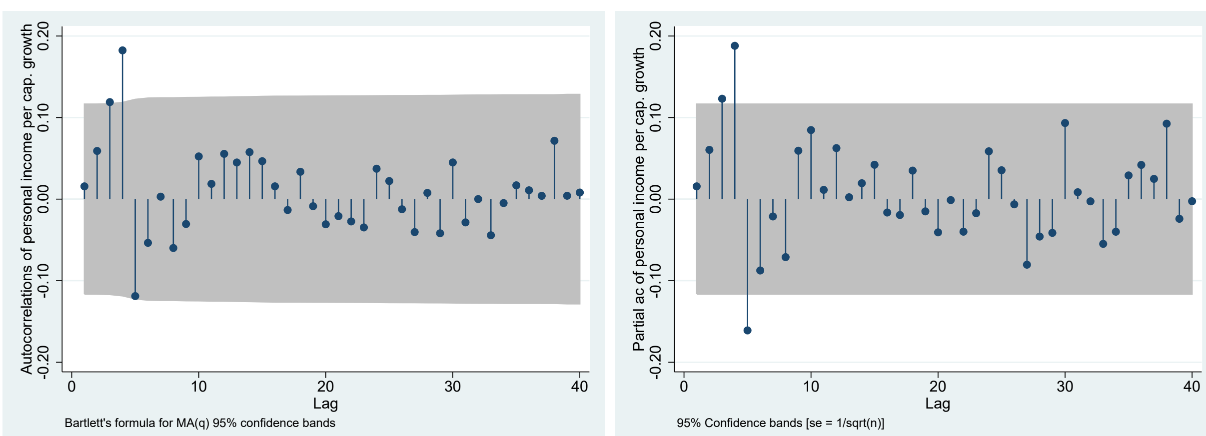

Figure 3.6: Autocorrelation function (left) and partial autocorrelation function (right) of Floridian deseasonalized personal income par capita growth.

Then, the second step is to estimate the model. To do this, the optimal number of lags to be included in the model can be determined using the ACF plot of g_t. The latter plot recommends a number of lags comprised between 3 and 5. Another alternative is to perform optimal lag tests. In this paper, four of them are selected, namely, the Final Prediction Error (FPE), Akaike information criterion (AIC), Hannan-Quinn criterion (HQIC) and Schwarz information criterion (SIC). The estimated optimal lag length corresponds to the one minimizing the criterion. The advantage of these optimal lag tests is to include the exogenous variable in the estimation. Table 3.8 presents the results of the tests. FPE, HQIC and SIC all suggest 5 lags, which somehow joins the interpretations made with the ACF plot, while SIC suggests that no lag should be included. Hence, considering altogether the results of the ACF, the PACF and those of the optimal lag tests, we choose to estimate the impact with 5 lags.

Table 3.8: Optimal lag tests for personal income per capita growth

	Final Prediction Error (FPE)	Akaike information criterion (AIC)	Hannan-Quinn criterion (HQIC)	Schwarz information criterion (SIC)
Nb lags				
0	.000148	-5.97863	-5.96739	**-5.9507***
1	.000148	-5.97778	-5.96092	-5.93588
2	.000148	-5.98358	-5.9611	-5.92771
3	.000147	-5.98817	-5.96008	-5.91834
4	.000145	-6.0039	-5.97019	-5.92011
5	**.000143***	**-6.01646***	**-5.97712***	-5.91869
6	.000144	-6.00882	-5.96387	-5.8971
7	.000145	-6.00165	-5.95108	-5.87596
8	.000145	-6.00022	-5.94403	-5.86056
9	.000146	-5.99685	-5.93504	-5.84322

Notes: * denotes the optimal number of lags to be included according to a given criterion. Estimations with a maximum number of lags fixed at 30. $\overline{Cyc}_{i,q}$ exogenous variable.

Finally, Table 3.9 outlines the results. Across all estimations, Floridian economic activity is found to be adversely affected one quarter after a cyclone strike, and this negative impact is muted afterwards with most of the specifications. According to the AIC and BIC criteria, the ARIMAX $(5, 0, 2)$ model seems to provide the best fit. A one km/h increase in the cyclone intensity measurement is responsible for 0.005 percentage points of growth loss in the quarter the tropical cyclone strikes Florida (significant at the 10% level). The point estimate two quarters later is also found to be negative and significant at the 10% level (-0.006 percentage points). For all the regressions, the invertibility condition is verified, meaning that all the roots of polynomials in lag operators lie inside the unit circle.

In order to prove that there is a differential impact across states, and that high exposure to tropical cyclones is not the only criterion that is responsible for a local negative impact, in Appendix C, we examine the results using the same methodology for North Carolina, Louisiana and Texas. The preferred specification according to AIC and BIC criteria is ARIMAX(4,0,0) for North Carolina, ARIMAX(1,0,2) for Louisiana, and ARIMAX(1,0,0) for Texas. In no case a significant impact is found for these three states.

4.2 County level analysis

All the results obtained at county level using a spatial autocorrelated model estimator are shown in Table 3.10. We decide to include 3 lags of the cyclone indicator in order to provide insights about longer-term effects. When using our cyclone intensity measurement $\overline{Cyc}_{c,t}$, the impact is consistently negative and significant over three years. The estimated immediate effect is -0.005 percentage points of growth for each km/h increase in storm intensity, -0.002 one year later, and then -0.003 two years later. The impact after three years is insignificant. If tropical cyclones are proxied by the share of the exposed population over each county, the immediate impact is comparable in magnitude but loses its statistical significance. However, the impact is larger in magnitude with better statistical significance one and two years after the occurrence of

Table 3.9: Results for regressing quarterly growth on cyclone indicator

	ARIMAX $(5,0,0)$	ARIMAX $(5,0,1)$	ARIMAX $(5,0,2)$	ARIMAX $(5,0,3)$	ARIMAX $(5,0,4)$
$\overline{Cyc}_q$	-0.00004	-0.00006*	**-0.00005***	-0.00005*	-0.00005*
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
$\overline{Cyc}_{q-1}$	0.00002	-5.02e-06	-7.58e-07	3.29e-06	-1.45e-06
	(0.00003)	(0.00003)	(0.00003)	(0.00004)	(0.00004)
$\overline{Cyc}_{q-2}$	-0.00004	-0.00007*	**-0.00006***	-0.00006	-0.00006
	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
$\overline{Cyc}_{q-3}$	-0.00002	-0.00003	-0.00003	-0.00005	-0.00004
	(0.00004)	(0.00003)	(0.00004)	(0.00004)	(0.00004)
$\overline{Cyc}_{q-4}$	-0.00001	-0.00003	-0.00003	-0.00003	-0.00003
	(0.00003)	(0.00006)	(0.00003)	(0.00003)	(0.00003)
$\overline{Cyc}_{q-5}$	7.16e-06	-9.35e-06	-7.03e-06	-1.02e-06	2.10e-06
	(0.00003)	(0.00004)	(0.00003)	(0.00003)	(0.00003)
AIC	-1201.304	-1203.568	**-1205.651**	-1204.697	-1201.396
BIC	-1158.169	-1157.114	**-1159.198**	-1154.925	-1144.988

Notes: robust standard errors in parentheses.
* significant at 10 %; ** significant at 5 %; *** significant at 1 %

the catastrophe. Finally, the frequency of events in Floridian counties has no impact, whether in the short- or long run according to our model. One might additionally notice that the coefficient associated with the spatially lagged error term is now negative across all our estimations. This negative influence of neighboring counties in errors does not change the influence on the results in comparison with positive coefficients obtained so far. Ignoring this parameter would keep consistent estimates of regression coefficients but these estimates would become inefficient. It would also lead to the estimation of biased standard errors. As in the last subsection, we replicate the estimations for North Carolinian, Louisianian, and Texan exposed counties with our main cyclone intensity measurement. Point estimates are still mostly insignificant, except one and two years later in North Carolina, for which a positive impact is found (+0.002 and +0.001 percentage points, respectively) and the second cyclone lag's point estimate for Texas (+0.004 percentage points). These positive and significant delayed impacts suggest the efficiency of recovery processes after a cyclone strike, even though the immediate impact is, in each case, insignificant. This might also mean that tropical cyclones actually stimulate local economic activity one and two years later. Regarding this point, one can rightly think that this absence of immediate effect and positive longer-run effect might be due to a mixed effect of the storm shock along with federal aid programs for reconstruction. In this regard, we analysed Federal Emergency Management Agency's data on hazard mitigation assistance from 1989 to 2020, *i.e.* funding for reducing disaster losses distributed by the federal government. During this period, Florida received 1.6 billion U.S. dollars while North Carolina got 1.4 billion, Texas 884.9 million and Louisiana 294.6 million U.S. dollars. Even though further investigation into the role of disaster assistance programs is required to determine their true effect, these descriptive statistics suggest that Florida benefits most from it, but does not manage to counteract the adverse effects of tropical cyclones one or two years later. The positive and statistically significant point estimates at county level in North Carolina or Texas or the absence of effect at State level in these States as well as in Louisiana might therefore not be fully explained by the transfers perceived to rebuild and reduce long-term risk.

Table 3.10: Results for regressing annual Floridian counties' growth on cyclone variables

	Independent variable $x = \overline{Cyc}_{c,t}$ (1)	Independent variable $x = Pop.\ Exposed_{c,t}$ (2)	Independent variable $x = Nb.\ Cyc_{c,t}$ (3)
$ln(Pers.Inc.pc)_{i,t-1}$	-0.047***	-0.047***	-0.046***
	(0.005)	(0.005)	(0.005)
$x_{c,t}$	-0.00005*	-0.00005	-0.0007
	(0.00004)	(0.00007)	(0.0007)
$x_{c,t-1}$	-0.00002*	-0.002***	0.0002
	(0.00001)	(0.0008)	(0.0008)
$x_{c,t-2}$	-0.00003***	-0.003***	-0.002
	(9.85e-06)	(0.0008)	(0.0008)
$x_{c,t-3}$	6.09e-06	-0.0003	-0.0009
	(9.27e-06)	(0.0008)	(0.0008)
ρ	0.106***	0.105***	0.106***
	(0.007)	(0.007)	(0.007)
λ	-0.088***	-0.086***	-0.089***
	(0.012)	(0.013)	(0.011)
Overall R^2	0.00	0.00	0.00
Observations	3283	3283	3283
Number of counties	67	67	67

Notes: Spatial autocorrelated model estimator with two-way fixed effects. Robust standard errors are in parentheses. Time and county fixed effects are included, but not reported in the table.
Significance levels : *** 1% ; ** 5% ; * 10%.

5 Conclusion

Tropical cyclones are fast onset and hardly predictable disasters, which have a tremendous potential to disrupt societies. This paper evaluates their impact on U.S. economic growth at county and state levels. Using 0.1° latitude × 0.1° longitude pixel level cyclone data, we build a measurement of disaster intensity which include both wind speed and share of exposed population. Data on personal income per capita come from the Bureau of Economic Analysis, which releases annual data at county level and quarterly data at state level. As the economic activity of a given area is undoubtedly influenced by those of its neighbours, our panel data estimations consider spatial correlations across groups, which are incorporated either by using spatial error models or spatial autocorrelated models.

Our first strand of results suggests that tropical cyclones do not influence economic activity in the U.S. when counties or states are sampled all over the country. However, in its second part, this study focuses on Florida State and its counties. Florida presents several factors of vulnerability to tropical cyclones. In particular, it is the most frequently exposed state in the U.S. Analyses are conducted using time series modeling for the single-state investigation, while the econometric strategy remains unchanged for the estimations within counties. This last series of estimations unveils significant results of growth depletion. On the quarter the cyclone occurs, the effect of a one km/h increase in intensity is to decrease contemporaneous growth rate by 0.005 percentage points, and by 0.006 more two quarters later. At county level, we estimate that such an increase in cyclone intensity is responsible for 0.005 percentage points in growth reduction on the year the cyclone occurs, and this negative effect remains significant up to two years after the strike.

Hence, our findings add to the recent body of literature that claims for regional or local investigations in environmental economics as we demonstrate the heterogeneity of causal effects within the same country in the context of tropical cyclones. Besides, it shows the relevance of using spatial econometrics such studies. Channels through which cyclone shocks propagate spatially surely deserve more exploration in the future. Further research on economic channels such as sectoral growth is required to better understand the observed growth reduction in Florida and bring more external validity to the present results.

Appendix of Chapter 3

A Specification test

Spatial dependence models are relevant models in the presence of cross-section of countries, regions, states, or more generally, any geographic units. In fact, introducing spatial effects in panel models leads models to take into consideration the interdependence between groups. It also allows to estimate spillover effects or externalities. These models are particularly attractive when dealing with regional science or urban economics issues. One can write a general equation for spatial panel data models as:

$$y_{i,t} = \alpha + \rho \sum_{i \neq j} w_{i,j} y_{j,t} + \beta x_{i,t} + \theta \sum_{i \neq j} w_{i,j} x_{j,t} + \mu_i + \delta_t + u_{i,t}$$

$$u_{i,t} = \lambda \sum_{i \neq j} w_{i,j} u_{j,t} + \varepsilon_{i,t}$$

with $y_{i,t}$ dependent variable, $x_{i,t}$ explanatory variable, and $w_{i,j}$ element of the spatial weighting matrix $W_N \in \mathbb{R}^{N \times N}$ that defines the neighboring links between each of the N groups.

Based on this general equation, we can define the following models:

- Spatial Autoregressive Model (SAR), if $\lambda = \theta = 0$.
- Spatial Durbin Model (SDM), if $\lambda = 0$.
- Spatial Autoregressive Model with Auto Regressive disturbances (SARAR), which are also called spatial autocorrelated model (SAC), if $\theta = 0$.
- Spatial Error Model (SEM), if $\rho = \theta = 0$.

Apart from these four basic models, many other specifications can be defined such as those with μ_i random and depending on spatial lags, dynamic models, etc.

In order to find the most appropriate model, some specification tests can be run using parametric statistical measures such as Wald tests. For instance:

- After estimating a SDM, one can check whether $\theta = 0$. If the null hypothesis is accepted, then it means that in fact, the appropriate model is a SAR.
- After estimating a SDM, one can check whether $\theta = -\beta\rho$. In this case, not rejecting the null hypothesis calls for a SEM model.

Table A.3.1 examines the results obtained for states with a SDM. In each case, the coefficients associated with the spatial lags of regressors are always insignificant, and the equality $\theta = -\beta\rho$ is verified. Altogether, this means that the correct model for state level analyses is the SEM. However, as for county level estimations, all $\theta = -\beta\rho$ Wald-type tests are rejected (p-value < 0.10), and spatially weighted independent variables' coefficients are found to be zero. Hence, we exploit a generalization of the SAR model, namely the SAC model.

Table A.3.1: Results for regressing quarterly State growth on cyclone intensity using a Spatial Durbin Model

	All states (1)	Exposed states (2)	Coastal states (3)
Wg	0.398***	0.252***	0.146***
	(0.012)	(0.015)	(0.022)
$ln(Pers.Inc.pc)_{i,t-1}$	-0.038***	-0.025***	-0.019***
	(0.003)	(0.003)	(0.003)
$\overline{Cyc}_{i,t}$	5.93e-07	2.69e-06	9.49e-06
	(0.00001)	(9.86e-06)	(0.00001)
$W\overline{Cyc}$	-1.00e-06	4.68e-06	6.90e-06
	(0.00002)	(0.00001)	(0.00002)
Observations	9792	7548	3876
Number of states	48	37	19
Overall R^2	0.00	0.00	0.00
Wald-type test $P > \chi^2$ θ = -$\rho\beta$	0.958	0.263	0.851

Notes: Spatial Durbin Model estimator with two-way fixed effects. Robust standard errors are in parentheses. Time and state fixed effects, as well as lagged per capita income spatial lags are included, but not reported in the table.

Significance levels : *** 1% ; ** 5% ; * 10%.

B Additional estimations

Table B.3.1: Results for regressing quarterly state growth on cyclone intensity using a specification that includes lags

	All states (1)	Exposed states (2)	Coastal states (3)
$ln(Pers.Inc.pc)_{i,q-1}$	-0.034***	-0.021***	-0.020***
	(0.003)	(0.002)	(0.003)
$\overline{Cyc}_{i,q}$	1.12e-06	6.61e-06	0.00001
	(0.00001)	(7.64e-06)	(8.21e-06)
$\overline{Cyc}_{i,q-1}$	-2.35e-06	3.12e-06	9.17e-06
	(0.00001)	(7.73e-06)	(8.31e-06)
$\overline{Cyc}_{i,q-2}$	0.00001	5.32e-06	7.85e-06
	(0.00001)	(7.64e-06)	(8.23e-06)
$\overline{Cyc}_{i,q-3}$	2.97e-06	5.82e-07	-2.03e-06
	(0.00001)	(7.69e-06)	(8.23e-06)
λ	0.40***	0.25***	0.17***
	(0.01)	(0.02)	(0.02)
Overall R^2	0.00	0.00	0.00
Observations	9792	7548	3876
Number of states	48	37	19

Notes: Spatial error model estimator with two-way fixed effects. Robust standard errors are in parentheses. Time and state fixed effects are included, but not reported in the table. Significance levels : *** 1% ; ** 5% ; * 10%.

C Analysing the effects on other frequently exposed states

Table C.3.1: Results for regressing quarterly growth on cyclone indicator

	North Carolina ARIMAX $(4,0,0)$	Louisiana ARIMAX $(1,0,2)$	Texas ARIMAX $(1,0,0)$
$\overline{Cyc}_t$	-0.00004	-0.00006	-0.00007
	(0.00003)	(0.00004)	(0.00005)
$\overline{Cyc}_{t-1}$	0.00003	-0.00001	0.00001
	(0.00003)	(0.00004)	(0.00004)
$\overline{Cyc}_{t-2}$	-0.00005		
	(0.00008)		
$\overline{Cyc}_{t-3}$	-5.57e-06		
	(0.00003)		
$\overline{Cyc}_{t-4}$	0.00002		
	(0.00003)		
$\overline{Cyc}_{t-5}$			
AIC	-1147.242	-1222.514	-1226.827
BIC	-1110.743	-1202.605	-1210.237

Notes: robust standard errors in parentheses.
* significant at 10 %; ** significant at 5 %; *** significant at 1 %

Table C.3.2: Results for regressing annual counties' growth on cyclone intensity

	North Carolina (1)	Louisiana (2)	Texas (3)
$ln(Pers.Inc.pc)_{i,t-1}$	-0.097***	-0.181***	-0.221***
	(0.006)	(0.010)	(0.006)
$\overline{Cyc}_{i,t}$	0.00002	0.00004	-0.00006
	(0.00002)	(0.00005)	(0.00008)
$\overline{Cyc}_{i,t-1}$	0.00002**	0.00002	0.00003
	(7.00e-06)	(0.00002)	(0.00003)
$\overline{Cyc}_{i,t-2}$	0.00001**	-1.43e-06	0.00004*
	(5.96e-06)	(0.00001)	(0.00003)
$\overline{Cyc}_{i,t-3}$	4.98e-06	0.00001	0.00002
	(5.38e-06)	(0.00001)	(0.00002)
ρ	0.118***	0.080***	0.064***
	(0.005)	(0.011)	(0.003)
λ	-0.079***	0.038***	0.064***
	(0.009)	(0.014)	(0.003)
Overall R^2	0.00	0.00	0.01
Observations	4900	3136	9751
Number of counties/parishes	100	64	199

Notes: Spatial autocorrelated model estimator with two-way fixed effects. Robust standard errors are in parentheses. Time and county fixed effects are included, but not reported in the table.
Significance levels : *** 1% ; ** 5% ; * 10%.

Chapter 4

The impact of tropical cyclones on income inequality in the U.S.: an empirical analysis

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Abstract

Despite a growing number of studies on the effects of tropical cyclones on economic growth, not much is known about their effects on income inequality. This paper addresses this question by using a panel data set of U.S. counties affected during the period 2010 - 2019. It exploits geophysical information to construct the disaster intensity predictor, and shows that storm shocks significantly decrease local income inequality levels in the year that they occur. A close study of the composition effects reveals several interesting patterns. First, the immediate impact is driven by the two lowest quintiles and the top quintile of the income distribution. Second, the beneficial effects on income inequality are stabilised in the short-run and the frequency of events is a crucial parameter to consider as repeatedly exposed counties exhibit larger responses after a cyclone strike than their rarely exposed counterparts. Finally, among others, this study stresses the importance of social safety nets in counteracting tropical cyclones' adverse income distributional effects.

Keywords: Natural disasters; Tropical cyclones; Income inequality; Economic impacts; Environmental risk
JEL classification: Q54; O15; D63

1 Introduction

With a total cost for weather and climate disasters in the U.S. rising to record levels in recent years according to the National Oceanic and Atmospheric Administration, contributing to debates on socio-economic impacts in the wake of these events has never been more pressing for economists. This paper specifically focuses on tropical cyclones, which are arguably the most deadly and destructive ones, and their effects on income inequality in the U.S. context.

Recent literature has brought substantial evidence of negative effects of these extreme events on economic growth at worldwide scale (Krichene & al., 2021; Kunze, 2021), or locally as in Strobl (2011) with negative impacts stressed in a U.S. panel cross-county study. While evaluating growth effects of tropical cyclones represents the dominant empirical approach, other externalities generated by these disasters barely remain unexplored. Among potential externalities, income inequality might be one of the most concerning. In fact, beyond the increasing attention it received from researchers, income inequality has also become a public concern ever since the Occupy Wall Street movement in New York in 2011, which has then been emulated worldwide (*e.g.* yellow vests protests in France since 2018, the Chilean social outburst from 2019 to 2021 etc.). Moreover, as expressed by Karim & Noy (2016), the direct impact of natural disasters must go further than analysing cross-country distribution of costs and economic activity, and effects across households with various income levels within a country could bring worthwhile insights into the literature.

There are reasons to believe that U.S. local income inequality patterns can be altered by cyclone shocks. First, a number of studies stress how hurricanes can affect local labour markets (Belasen & Polachek, 2009; Coffman & Noy, 2012; Deryugina, 2017; Groen & al., 2020). Then, Fothergill & Peek, (2004) claim that the poor are more vulnerable to natural disasters in the United States, and more specifically due to their place and type of residence, the quality of building construction, or social exclusion. In addition to the differential impact between low- and rich-income populations, income inequality can be impacted by how people or governments cope with such extreme events, and to what extent the associated risk is shared within the population. As a matter of fact, tropical cyclones, and more generally natural disasters, are surely a source of socio-economic disruptions. In the social resilience theory, the concept of panarchy (Allen & al., 2014) states that these disturbances of wealth and power can have sizeable effects on inequality levels *via* the management of economic recovery processes and subsequent political decisions taken by the public authorities. In order to mitigate the adverse effects of tropical cyclones, reallocation of resources and redistribution mechanisms are triggered either between affected and non-affected areas, or within affected areas. For instance, government disaster and non-disaster related aid programs can be seen as a transfer from one taxpayer to another (Kousky, 2014). Natural disasters can therefore influence public sector corruption (Yamamura, 2014), but also social cohesion or societal trust (Toya & Skidmore, 2014) which can, in turn, affect inequalities within populations of a same country.

All this being said, however, having expectations on whether natural disasters and income inequality are positively or negatively associated is a very arduous task. As argued by Keerthiratne & Tol (2018), on the one hand, poor households possess little that can be lost to a natural disaster, unlike wealthier ones who are endowed with much more material assets. Business owners are likely to face an adverse income shock resulting from business interruptions, which are either due to direct damages or indirectly due to a break in the supply chain, whereas low-skilled or unskilled labourers may not go through a monthly wage decline as they may quickly find new opportunities in the construction sector or expand their income sources. On the other hand, poor households are more likely to live with irregular income, and thus, are more subject to losses compared to rich ones.

Besides, results reported in the literature are mixed and reveal to greatly depend on the country studied or the scale chosen. Using the 2008 Vietnam Household Living Standard Survey, Bui & al. (2016) find that natural disasters increased national income inequality. In the Bangladeshi case, Abdullah & al., (2016) find a decrease in regional income inequality in the Sundarbans after Cyclone Aila in 2009. Yamamura (2015) concludes on a short-run increasing effect of natural disasters on income inequality using a worldwide panel data set, but no longer-term effect. Feng & al. (2016) state that the 2008 Sichuan earthquake in China had no effect on income inequality, even though the average income of households dropped substantially. Keerthiratne & Tol, (2018) find a beneficial effect of natural disasters on Sri Lankan income inequality levels between 1990 and 2013 using household survey data. More recently, in the German case, Reaños (2021) simulates expected flood damages under multiple fiscal scenarios and suggests that, overall, floods increase income inequality. Finally, as for studies carried out in the U.S., anticipating the direction of the relationship reveals to be even more tricky. First, while some single-event studies suggest that hurricaines are negatively associated with earnings in the short-run but positively associated in the long-run (Groen & al., 2020), other longitudinal studies on a series of hurricane events either find a positive relationship (Belasen & Polachek, 2009) or no significant effect (Deryugina, 2017). Then, in the more general context of natural disasters, Pleninger (2022) exploits the Current Population Survey and concludes on a negative income effect of disaster strikes in U.S. counties for people with middle incomes, which translates into an absence of effect on the Gini index. This study proposes, to date, the empirical exercise that is the most related to ours within the existing literature. We argue that the present paper constitutes a strong complement to these results as we focus on one type of natural disaster, namely tropical cyclones, and thereby offer a perspective to unravel the heterogeneity in these general results. In fact, natural disasters might differ by their outcomes on an economy. For instance, droughts are considered as the deadliest catastrophes worldwide from 1970 to 2019 while tropical cyclones are the costliest ones (WMO, 2021). In addition, some types of disasters such as floods or landslides might be the consequence of prior tropical cyclone formations, and thus, losses due to natural disasters might be the result of cumulative processes. Accordingly, the magnitude of a natural disaster's impact on an economy undoubtedly depends on its characteristics, especially its intensity. As we also properly consider the latter dimension, we hope that the present study will make a significant contribution to the literature.[1]

To characterise the distributional effects of tropical cyclones, we exploit a geophysical data set in order to build a physical measure of disaster intensity. In this paper, tropical cyclone shocks consist of a two-pronged approach as it considers the intensity of storm events in terms of wind speed and the exposure within each county using the share of exposed population. Tropical cyclones' effects can be felt over large areas surrounding their centre, and thus, their spatial structure and movements are estimated with an appropriate wind field model. Information on their overall trajectory is provided with respect to their exact latitude and longitude coordinates. Our measures of income inequality come from detailed household-level data from the American Community Survey (ACS) 1-year estimates, available from 2010 to 2019. This data set allows us to consider different inequality measures (share of the bottom 60% of aggregate household income, share of

[1] Pleninger (2022) uses a dummy variable to express the occurrence of at least one natural disaster during a year, and evaluates the effect of "severe" disasters by restricting to those that resulted in at least 10 deaths among the population during a given year. However, this definition of severity might raise reverse causality bias concerns, as some studies suggest that human costs are negatively correlated with GDP per capita (Kahn, 2005; Felbermayr & Gröschl, 2014). As inequality levels are relatively high in the United States compared to other developed countries, it is likely that the deadliest disasters mainly occurred in poorest areas. To overcome this issue, Noy (2009) recommends to express the intensity of disasters by using only physical indicators.

the two lowest quintiles, share of the lowest quintile, share of the top quintile, share of the top 5% of the distribution, Gini index) to test whether tropical cyclones have redistributive effects at the county scale. All in all, we obtain an unbalanced panel of 540 counties, which were all affected by storm events from 2010 to 2019. Our key empirical exercise consists of dynamic panel data regressions which include year and county fixed effects to control for common time trends, institutional differences across counties or their geographical location. Given the shortness of our panel and a fairly large number of counties, we use a two-step system GMM approach (Arellano & Bover, 1995; Blundell & Bond, 1998). Our results are noteworthy as we provide evidence that tropical cyclones reduce income inequality in the year that they occur. However, point estimates are low in magnitude, meaning that tropical cyclones cannot be considered as an important determinant of income inequalities. Further exploration indicates that the two lowest quintiles of the income distribution and the top quintile, are those driving this favorable impact. Then, we conclude that income inequality does not decrease further one year after the cyclone strike, but the contemporaneous impact is not counteracted either in following years as the cumulative impact after two years remains negative and significant, with almost same magnitude. This result additionally shows that having already experienced a catastrophe one or two years before is beneficial, as introducing lags to the baseline equation intensifies tropical cyclones' contemporaneous effect on income inequality. In a final extension, we address the issue of transmission mechanisms. In line with Deryugina (2017), but also Pleninger (2022), this investigation suggests the presence of post-disaster spending adjustments in favor of the poorest as well as capital income losses for higher income groups. Lastly, one can rightly think that, as tropical cyclones are a major threat to physical capital, analysing their effects on wealth inequality might also be of great importance. In this regard, as wealth accumulation mainly depends on earned income and is not only determined by the stock of assets owned at some point in time, the issue of how income inequality effects can be measured seems like a preliminary question to be solved. Hence, we believe that our results constitute a first step in the direction of wealth inequality concerns, but also in determining what kind of policies or income sources within quintiles can more accurately explain how these extreme weather events impact income inequality. Yet, this paper contributes to make the link between Strobl's (2011) local negative growth impact of tropical cyclones and the positive relationship found between income inequality and economic growth in the U.S. by Rubin & Segal (2015).

The remainder of the paper is organised as follows. Section 2 introduces the data. More specifically, it discusses the construction of our cyclone intensity measurement as well as income inequality measures, and provides descriptive statistics. Section 3 describes the estimation strategy, presents the main results on the impact of tropical cyclone shocks on local income inequality, and considers a series of robustness checks. Section 4 analyses more deeply the distributional effects, documents on timing effects and studies how the impact shifts given exposure levels. This section also discusses potential channels through which tropical cyclones affect income inequality. Section 5 concludes.

2 Data

In this section, we first describe the data set on tropical cyclone records as well as the construction of the county-by-year cyclone intensity measurement. Then, we present the American Community Survey, the set of local income inequality measures and other economic variables extracted from it for the purpose of this paper.

2.1 Cyclone data

The Tropical Cyclone Exposure Database

Data on cyclone events in the U.S. are taken from Tropical Cyclone Exposure Database (TCE-DAT; Geiger & al., 2018), with an extension up to 2019 kindly provided by the research team upon request. TCE-DAT is a comprehensive historical data set on each landfalling tropical cyclone event worldwide from 1950 to 2019. To meet the needs of this paper, we only retain those affecting the U.S. at some point of their trajectory. TCE-DAT first compiles data from the International Best Track Archive for Climate Stewardship (IBTrACS; Knapp & al., 2010), which is released publicly by the National Climatic Data Center of the National Oceanic and Atmospheric Administration (NOAA). For each cyclone centre (called the "eye"), IBTrACS reports information on latitude and longitude position, wind speed, surface air pressure and trajectory (*via* 6-hourly observations). This information is then used as input in Holland's (2008) widely used wind field model in order to get an overall cyclone trajectory and intensity at 0.1° latitude x 0.1° longitude grid cell level for each event recorded in the IBTrACS database with wind speeds of at least 34 knots ($\approx$ 63 km/h) and sustained at least one minute. A cyclone is considered as landfalling if at least one grid cell of the U.S. is affected by the simulated wind field. This means that even storms for which the eye does not make landfall but still passes by near enough the U.S. coasts to be felt are included in the data set. All in all, TCE-DAT identifies 314 cyclone events during the period 1950 - 2019, and among them, 46 occurred during our period of study (2010 - 2019).

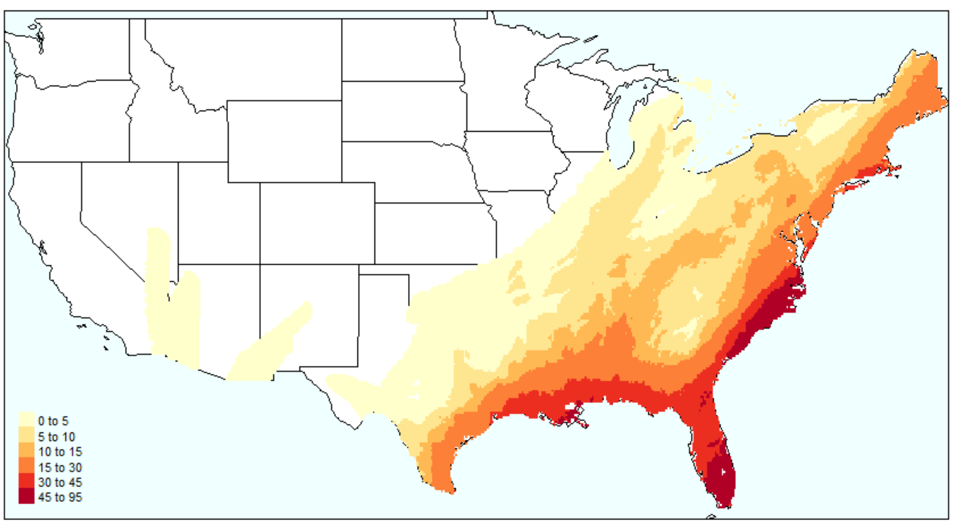

Figure 4.1: Yearly average wind speed intensity (in km/h) in the contiguous U.S. between 1950 and 2019

Figure 4.1 maps the yearly average wind speed felt at pixel level in the contiguous U.S. from 1950 to 2019. Storms are more intense along coastal areas, and lose their power once they get deeper in lands because of increasing frictional forces and the loss of storms' main source of energy which is water. This map also illustrates the existence of strong inequality in terms of exposure within the country. As a matter of fact, Florida is the most frequently hit state of the U.S., with

118 cyclone events between 1950 and 2019, while Kansas has only been affected once during the same period (Figure 4.2).

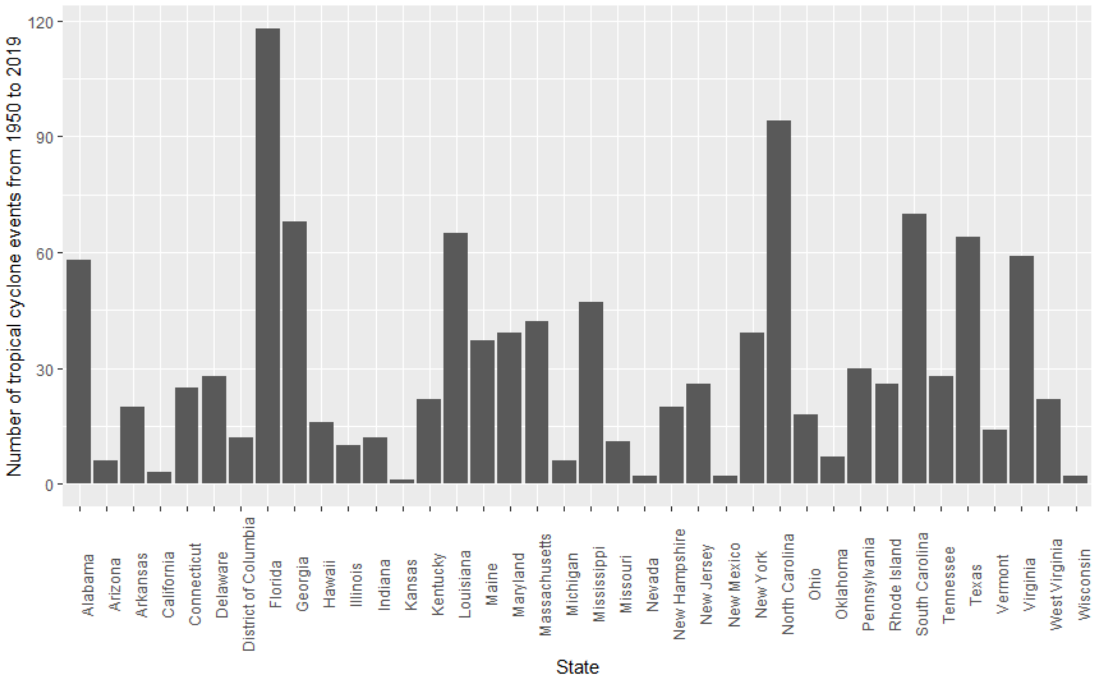

Figure 4.2: Number of storm events in the U.S., by state, between 1950 and 2019

Physical measure of cyclone intensity

TCE-DAT's pixel-event level data are rescaled and brought to county-year level in order to fit with our cross-county panel data framework. Since our purpose is to assess counties' vulnerability regarding income inequality, it is essential to consider the levels of exposure within each county in addition to local wind speed estimates. To do this, we exploit another strand of the data set, which is the gridded estimates of exposed population. In the end, this makes us able to build a physical measure of cyclone intensity. This scale-free indicator can be expressed as follows:

$$\overline{Cyc}_{c,t} = \frac{\sum_{p=1}^{P_c} \max_{s\in\{1,\ldots,S_{p,c,t}\}} \{Wind_{p,s,c,t}\} \left(\frac{12-m_{p,s}}{12}\right) Exposed\ Population_{p,t}}{Total\ Population_{c,t}} \tag{4.1}$$

where $Wind_{p,s,c,t}$ is the wind speed recorded in pixel p, for storm s that struck county c in year t. $Exposed\ Population_{p,t}$ corresponds to the estimated population in pixel p and reported in TCE-DAT, while $Total\ Population_{c,t}$ is the number of inhabitants in county c during year t as estimated in the American Community Survey (1-year estimates). Following the approach of Noy (2009), we also include a temporal weight $(12 - m_{p,s})/12$, with $m_{p,s}$ the month in which the storm occurred. This additional feature enables to capture the contemporaneous impact with more accuracy as a cyclone that strikes in the early months of a given year has arguably a bigger impact in the same year than another one - with same intensity - occurring some months later. This monthly weighting is all the more important since tropical cyclones mostly occur in the second part of the year.

One might notice that the pixel level wind speed is selected as the maximum wind speed value felt in each year t, irrespective of the number of cyclone events $S_{p,c,t}$ identified within each pixel for the given year as in Felbermayr & Gröschl (2014). Regarding this methodological choice, it can be argued that since the replacement of destroyed capital needs more than one year to be effective, the occurrence of less devastating cyclones within the same year is considered as negligible.

In sum, this indicator corresponds to a population-weighted average of the maximum sustained wind speed over all pixels P_c contained in county c. Such normalisation approach is in line with Nordhaus (2006) as it aims to determine the average effect of storm events on an average pixel for a given county. To a slightly lesser extent, using such a population-weighted disaster measure can also help to capture where the economic activity is more intense. This measurement is quite similar to the one established by Hsiang & Jina (2014) and can be thought as an estimate of a cyclone's average intensity in a randomly selected unit of land for each county, or the value of a given cyclone's intensity if this one had struck the county homogeneously across all its locations.

Last but not least, this class of indicators must be distinguished from economic-based indicators such as death toll, total amount of damages etc., which are subject to reverse causality bias and other sources of endogeneity coming from exploitable data sources.[2] Our physical disaster measure must also be differentiated from damage functions, which are assumed to be non-linear in wind speed. Even if it physically makes sense that damages can sharply increase with wind speed because of a subsequent energy dissipation blowout, finding a true damage function reveals to be unmanageable. In fact, while Nordhaus (2006) suggests that the relationship between wind speed and damages in the U.S. is around the eighth power, Strobl (2011) finds a coefficient around three.[3] To date, no general consensus emerges on this question and wide range of possibilities for the wind speed to damage correlation coefficient can exist. Moreover, an ultimate issue with a damage function approach revolve around the fact that most existing disaster loss data sets ignore indirect losses or damages to non-market goods and services (Kousky, 2014). As most data on losses generated by disasters probably underestimate their overall economic cost, we choose to rely on a physical storm measure based on local wind speed intensity. Tropical cyclones' damaging effects on physical capital can lead to infrastructure failures and business interruptions which, in turn, affect local labour markets and alter income inequality.

2.2 Macroeconomic data

The American Community Survey

Our income inequality data come from the American Community Survey (ACS), 1-year estimates. The ACS is a nation-wide survey maintained by the U.S. Census Bureau and provides social, economic, housing and demographic data every year. In the 1-year survey, information is collected almost every day of the calendar year from a very large sample that represents the U.S. civilian population, and among geographic areas with at least 65 000 inhabitants. For the purpose of this paper, we extract the shares of quintiles of aggregate household income as well as the Gini index of income inequality to construct our primary measures of local inequality. Data are available from 2010 to 2019. Aggregate income corresponds to the sum of all types of income considered in the ACS: wage or salary, self-employment, interest, dividends, net rental income, royalty income, or income from estates and trusts, social security or railroad retirement, supplemental security, public assistance, retirement, survivor, or disability, and all other periodic income

[2]See Felbermayr & Gröschl (2014) for a detailed discussion.

[3]Using a non-statistical methodology, Emanuel (2005) also finds a cubic relationship in the U.S. case.

other than earnings (unemployment compensation etc.). At household level, income is measured as the sum of householder's income and those of all other individuals' aged 15 and above who were members of the household at the time the interview was conducted. The Gini index is calculated from the household income distribution.[4]

Measures of income inequality

Hence, given the availability of household income data, the ACS allows us to study the behaviour of income inequality. Based on Kuznets & Jenks (1953) or Kuznets (1955), we focus on the following measures: the share of the bottom 60% of the aggregate income distribution, the share of the two lowest quintiles, the share of the lowest quintile, the share of the top quintile and the share of the top 5% of the distribution. Top income shares have a fairly different income composition than bottom ones, and are often of particular interest in studies on income inequality (Atkinson, Piketty & Saez, 2011). In addition, we also consider the Gini index, which remains a widely used synthetic indicator and explains the extent to which household income is equally allocated or deviates from a purely proportionate distribution.

Other macroeconomic variables

In order to provide understanding of the transmission channels through which tropical cyclones can affect local income inequality, we exploit more macroeconomic variables coming from the ACS. In particular, we are interested in employment shares for populations respectively below and above the poverty line, and several components of aggregate income. For the former class of variables, the ACS' poverty thresholds are determined in accordance with three criteria: the size of family, the number of children, and, for one- and two- person families, the age of the householder. As for income components, we make a distinction between wage and salary income, and earnings which includes both wage and salary income as well as self-employment income. Then, we also extract information on interest, dividends, net rental income or income obtained from estates and trusts, which serves as a proxy for capital income. Finally, we include the data on other types of income, which is constructed with answers to the section "any other sources of income received regularly such as Veterans' (VA) payments, unemployment compensation, child support or alimony" appearing in the survey form. In what follows, this residual type of income is considered as a proxy for the amount unemployment benefits perceived by households. It seems reasonable to assume that the amount of VA, child support or alimony benefits are unrelated to the occurrence of a tropical cyclone.

2.3 Descriptive statistics

Table 4.1 provides summary statistics for our unbalanced panel of 540 counties which were all, at least once, affected by a storm from 2010 to 2019. The strongest cyclone event recorded during the sample period is hurricane Irene, which struck the East Coast of the U.S. in August 2011. According to our cyclone intensity indicator, York county in Virginia records the highest average wind speed value of the sample with 144.04 km/h during Irene, followed by Richmond in New York (136.83 km/h), and Hudson in New Jersey (136.82 km/h) during the same catastrophe. Income inequality statistics also show a great dispersion within the sample and across counties.

[4] For further details, see the subject definitions on `https://www.census.gov/programs-surveys/acs/technical-documentation/code-lists.html`

Kendall county in Illinois has the lowest Gini coefficient of the sample, with 0.33 in 2019, while the highest level of inequality is recorded for Putnam in Tennessee (0.63 in 2013). Kendall (Illinois) reveals to be the county with lowest income inequality as measured by all our set of inequality metrics. Putnam (Tennessee) shows the highest level of inequality across all metrics, except when analysing the share of the first quintile and the share of the two lowest quintiles, for which either Lowndes (Georgia) or New York (New York) have respectively the lowest value.

Table 4.1: Summary Statistics (N = 5335)

	Mean	Std. Dev.	Min.	Max.
$\overline{Cyc}_{c,t}$	6.13	14.88	0	144.04
Gini index	0.45	0.04	0.33	0.63
Bottom 60% share of aggregate income	27.95	2.64	17.13	37.05
Bottom 40% share of aggregate income	12.76	1.63	6.63	18.94
First quintile's share of aggregate income	3.60	0.66	0.52	5.92
Fifth quintile's share of aggregate income	48.63	3.35	37.69	64.83
Top 5% share of aggregate income	20.69	3.09	12.35	40.99
Share of employed population below poverty level	4.04	1.87	0.47	18.33
Share of employed population above poverty level	54.78	6.53	20.09	76.45
Wage or salary income (logged)	22.11	1.03	20.30	25.78
Interest, dividends or net rental income (logged)	19.22	1.20	15.59	23.17
Earnings (logged)	22.18	1.03	20.34	25.82
Other types of income (logged)	18.47	0.90	15.80	21.97

3 Effects of tropical cyclones on income inequality

In this section, we investigate whether U.S. local income inequality patterns from 2010 to 2019 varied with tropical cyclone shocks. We first discuss the model specification and the estimation methodology. Then, we present our baseline results for different income inequality measures.

3.1 Econometric specification

We opt for a dynamic panel data regression approach:

$$y_{c,t} = \gamma y_{c,t-1} + \beta \overline{Cyc}_{c,t} + \mu_c + \lambda_t + \varepsilon_{c,t} \tag{4.2}$$

where the subscripts c and t represent county and year, respectively. y is the income inequality measure, and $\overline{Cyc}_{c,t}$ corresponds to our population-weighted average of cyclone intensity as introduced in the previous section. μ_c denotes unobserved county-specific effects, and λ_t represents time-specific effects and captures common shocks across periods. ε is an independent and identically distributed (i.i.d.) error term with mean 0 and finite variance.

As we are in a context of a small and wide panel data set, *i.e.* a limited number of time periods and a large number of exposed counties, the estimation of (4.2) using the within-group estimator is undoubtedly inappropriate (Nickell, 1981). Besides, most existing studies consider tropical cyclones as strictly exogenous, which is debatable. In fact, even though the exact timing and trajectory of a storm cannot be exactly predicted in advance, the frequency and intensity of such a catastrophe and its impact in a given county can be correlated with unobserved variables such as the practice of local people (Bui & al., 2014), the influence of human-induced climate change (IPCC, 2022), or local economic preparedness. The latter point is crucial as the likelihood, or propensity of a county to be exposed and adversely affected by a hazard is one major feature that characterises its intrinsic vulnerability (Cutter, 1996; IPCC, 2022). To deal with both of these issues and avoid statistical shortcomings, we estimate the model using the generalized method of moments (GMM) procedure designed for dynamic panel specifications. Introduced by Holtz-Eakin & al. (1988), and subsequently enhanced by Arellano & Bond (1991), Arellano & Bover (1995) and Blundell & Bond (1998), these estimators consist of using previous observations of explanatory and lagged dependent variables as internal instruments in order to cope with the aforementioned endogeneity biases. As stated above, we also relax the assumption that tropical cyclones are strictly exogenous, that is, these extreme events are henceforth considered as unrelated to current disturbances but can be influenced by past ones.

We follow Arellano & Bover (1995) and Blundell & Bond (1998) and use the two-step system GMM estimator. This estimator corrects potential biases of the difference GMM estimator previously developed by Arellano & Bond (1991), especially when weak instruments are generated by persistent series. This procedure relies on a system of two regression equations, one is the first-differenced version of equation (4.2) to control for unobserved county-specific effects and the other one is the equation (4.2) in levels. The inclusion of this second equation, and thus of additional moment conditions, improves the precision of the estimator. Both equations are simultaneously estimated but distinctly instrumented. Instruments of the difference equation correspond to lagged levels of the explanatory variables, while the equation in levels is instrumented by the lagged differences of these variables. Under the resulting assumption that the correlation between the dependent variable and county fixed effects is time-invariant, the two-step system GMM procedure renders consistent and efficient estimates of the parameters of interest.

3.2 Results

One underappreciated issue behind the usage of system GMM method concerns instrument proliferation (Roodman, 2009). As a matter of fact, explanatory variables are instrumented separately for each time period, and the potential set of instruments for the difference equation grows quadratically with the number of time periods T. A large instrument count can overfit instrumented variables, and ultimately generate biased two-step estimates. It also weakens the Hansen J test of overidentifying restrictions, which tests for the instruments' joint validity. A high instrument count relative to the number of groups underestimates the statistic.[5] To cope with this, we limit the number of lags of each instrumenting variable to two. In addition, we also run Arellano-Bond tests of serial correlation applied to the error term in differences.[6]

Results of the baseline model are presented in Table 4.2. Overall, we find an immediate negative impact of tropical cyclones on income inequality, which seems to be driven by the poorest quintiles for whom the share of aggregate income rises compared to those at the top of the distribution. Nevertheless, magnitude of the coefficients is quite low. The share of the bottom 60% one raises by 0.006 percentage point for each additional km/h of cyclone intensity, while the share of the lowest

[5] For the J test, H_0 corresponds to a validation of the set of over-identifying restrictions. Thus, accepting the null hypothesis provides support to the model.

[6] Model specification is supported when the null hypothesis of the test is rejected for first-order serial correlation (*i.e.* presence of correlation), and accepted for second-order correlation.

Table 4.2: System GMM regression of income inequality on cyclone intensity.

	Bottom 60% share of aggregate income (1)	Bottom 40% share of aggregate income (2)	Gini index (3)	First quintile's share of aggregate income (4)	Fifth quintile's share of aggregate income (5)	Top 5% share of aggregate income (6)
$y_{c,t-1}$	0.055*	0.027	0.048	0.064**	0.032	0.011
	(0.031)	(0.031)	(0.030)	(0.030)	(0.031)	(0.027)
$\overline{Cyc}_{c,t}$	0.006***	0.004***	-0.00008***	0.001***	-0.006***	-0.001
	(0.002)	(0.001)	(0.00002)	(0.0004)	(0.002)	(0.003)
Observations	4795	4795	4795	4795	4795	4795
Number of counties	540	540	540	540	540	540
Number of instruments	57	57	57	57	57	57
Arellano-Bond test for AR(1) in first-differences	0.00	0.00	0.00	0.00	0.00	0.00
Arellano-Bond test for AR(2) in first-differences	0.96	0.87	0.36	0.34	0.33	0.34
Hansen test of overidentifying restrictions	0.33	0.77	0.28	0.56	0.08	0.04

Notes: All regressions are two-step system GMM. Standard errors clustered by counties and incorporating the Windmeijer (2005) correction are in parentheses. Time fixed effects are included in all specifications, but not reported in the table.
Significance levels : *** 1% ; ** 5% ; * 10%.

40% of the distribution increases by 0.004 percentage point. Both of these results are significant at the 1% level. This beneficial effect on income inequality is emphasised by the decrease observed in the Gini coefficient, which is our synthetic index. Each km/h increase in wind speed exposure over a county diminishes local Gini index by 0.00008, and this point estimate is significant at the 1% level. Put another way, a one standard deviation increase in the cyclone indicator ($\sigma_{\overline{Cyc}_{c,t}} = 14.9$) decreases the Gini coefficient by 0.001. As for the top income groups' share of income, the J test is rejected at the 10% level for the top quintile and at the 5% level for the top 5% and no conclusion can be drawn for them. These findings are consistent with the results reported in previous studies. More specifically, Strobl (2011) shows that hurricanes have a negative impact on economic growth in the U.S. at county level, and Rubin & Segal (2015) conclude that growth and income inequality are positively associated in the U.S..

Our main results are stable across a variety of robustness checks. To start with, in Appendix A, we check the robustness of these estimates to more drastic cuts in instrument count by "collapsing" them. We also re-estimate our model with a difference GMM method. In fact, losses of statistical significance when bringing our system GMM estimations back to difference GMM would suggest the presence of endogeneity biases (Roodman, 2009). We also check the validity of our results when withdrawing the lagged dependent variable from equation (4.2) and thereby using a fixed effects estimator. Finally, we check the consistency of the results when using fractional outcome models. In no case are the results altered by these changes in estimators, except for the impact on the bottom 60%'s share of income when collapsing instruments: the null hypothesis of the J test becomes rejected at the 5% level. Results on the top quintile and the top 5%'s share of income when using the static model stress the absence of impact on the richest households, even though we find statistical significance for the former group with a difference GMM approach or with collapsed instruments.

Secondly, in Appendix B, we present the estimates obtained when some features of our cyclone indicator are modified. Choosing the percentage of exposed population as disaster proxy in the spirit of Krichene & al. (2020) or Keerthiratne & Tol (2018), removing monthly weighting, or simply using maximum wind speed levels over each areas as Felbermayr & Gröschl (2014) does not change the results either. Once again, the top quintile intermittently shows statistically significant negative point estimates. Interestingly, removing the wind speed component leads to stronger effects, while these are lessened in the both other cases. Hence, these results further underline the importance of the choice of the metric in the magnitude and significance of the effects.

Thirdly, we check whether our results hold when including additional meteorological or economic control variables to equation (4.2), namely, temperature and precipitation, or income per capita growth and the share of poor households in the county (Appendix C). Across both extensions, we find that tropical cyclones and income inequality are still negatively associated, with almost similar point estimates of the disaster, but slightly varying statistical significance. The effect on the first quintile is now insignificant, though with a p-value lightly above 10%. Furthermore, it is interesting to notice the positive relationship between temperature and inequality. This point surely deserves further exploration in another study. The positive correlation between economic growth and income inequality is also verified within the present sample (coefficient of 0.016 for the Gini index, significant at the 10% level). However, our results cannot fully provide support for Rubin & Segal (2015): even though we find no link between economic growth and low-income shares, J tests are rejected at the 10% level for the top quintile's share of income and at the 1% level for the top 5% of the distribution.

As a last step, in Appendix D, we consider robustness to alternative samples. First, our main specification is repeated on a balanced sample, *i.e.* where all the counties are present in the sample for the entire 2010 - 2019 period. Estimates remain almost unchanged in terms of magnitude, but standard errors slightly increase, probably due to the fact that the amount of data in the model is reduced. Then, we expand the panel to include all the counties that were ever affected during the period 1950 - 2019. In fact, given the fat tailed nature of the tropical storms distribution presented in section 2, one can argue that our baseline sample may not be representative of the entire sample of counties actually exposed to cyclonic risk. It is likely that for many counties storms represent very rare events, but still devastating at some point in their history. All the counties that have not experienced a storm during our sample period of 10 years can even be thought as a pertinent control group, as they all remain potential targets and concerned by this issue, even though they were unaffected during this specific time period. Reconsidering the sample in such a way continues to show substantial negative effects on income inequality, with very few change compared to the baseline results. Finally, we pursue our controls for potential selection biases and re-run the analysis with the entire set of U.S. counties that are included in the ACS 1-year. The newly included 287 counties which were unaffected during the sample period can again be considered as quasi-control group whereas counties of the baseline sample are treated ones. Under this last framework, coefficients are smaller in magnitude but signs and statistical significance remain barely unchanged.

4 Disentangling composition effects

Thus far, our estimates stress that counties hit by a tropical cyclone experience a contemporaneous decrease in income inequality. In what follows, this result is further explored by bringing some extensions to equation (4.2). Firstly, we investigate the influence of each income quintiles in the above results. Then, we include additional lags of cyclone intensity to the main model and examine the impact of these extreme weather events over time. Finally, components of aggregate income are disaggregated and shares of employed population below and above the poverty level are analysed so that transmission mechanisms can be studied.

4.1 Which quintiles lead the contemporaneous effect?

In the baseline results, shares of bottom income quintiles are summed and studied as a whole in order to be consistent with the existing literature (Kuznets, 1955). Instead, this subsection explores the distinct impact across all quintiles and additionally if there is a monotonic behaviour among bottom ones, *i.e.* if $\beta_i \leq \beta_j, \forall\ quintile\ i < quintile\ j < quintile\ 4$, which would suggest a labour income effect. Table 4.3 shows the results. To facilitate reading and examination, estimates obtained for the first and fifth quintiles and presented in Table 4.2 are respectively repeated in the first and fifth column of Table 4.3. We find only partial evidence of a monotonic ordering of the effect as the coefficient associated to the second quintile is larger than the first one's, but results are invalid for the third and fourth quintiles (Hansen tests rejected at the 5% level).[7] Hence, the first, second, and top quintiles are those triggering the immediate decrease in income inequality observed on more aggregate indices. This table also suggests that shares of aggregate income in the middle of the distribution are unaffected by tropical cyclone events. These findings are partially consistent with Pleninger (2022) who demonstrates that income losses are increasing for higher income groups in the aftermath of hurricanes or storms.[8] Middle income groups may go through some income losses, but in the end, these losses do not translate into a significant loss in their aggregate income shares. However, as point estimates are not significant for the top 5% income share, our results shed light on the heterogeneous impact across top income share levels.[9]. This slight difference in results with Pleninger (2022) probably stems from the pooling of storms and hurricanes in the present paper, but also from the fact that our indicator captures the intensity of phenomena.

Table 4.3: System GMM regression of income inequality on cyclone intensity.

	First quintile's share of aggregate income (1)	Second quintile's share of aggregate income (2)	Third quintile's share of aggregate income (3)	Fourth quintile's share of aggregate income (4)	Fifth quintile's share of aggregate income (5)
$y_{c,t-1}$	0.064**	0.038	0.052*	-0.022	0.032
	(0.030)	(0.029)	(0.031)	(0.030)	(0.031)
$\overline{Cyc}_{c,t}$	0.0013***	0.0026***	0.0020***	-0.00069	-0.0061***
	(0.0004)	(0.0006)	(0.0008)	(0.00088)	(0.0023)
Observations	4795	4795	4795	4795	4795
Number of counties	540	540	540	540	540
Number of instruments	57	57	57	57	57
Arellano-Bond test for AR(1) in first-differences	0.00	0.00	0.00	0.00	0.00
Arellano-Bond test for AR(2) in first-differences	0.29	0.90	0.72	0.19	0.33
Hansen test of overidentifying restrictions	0.56	0.60	0.02	0.03	0.08

Notes: All regressions are two-step system GMM. Standard errors clustered by counties and incorporating the Windmeijer (2005) correction are in parentheses. Time fixed effects are included in all specifications, but not reported in the table.
Significance levels : *** 1% ; ** 5% ; * 10%.

4.2 Is there any lasting impact?

Another extension that can be made is to examine the persistence of the effects using a series of cyclone intensity measurement lags. As the contemporaneous impact is captured according to the month in which the storm occurred, we extend and adapt this monthly weighting to each additional lag that is included in the augmented version of equation (4.2). We introduce up to two

[7] The absence of impact on these two quintiles is confirmed by estimations using a static fixed effects model, with which point estimates are insignificant. These additional results are available upon request.

[8] In particular, she shows that the top decile of the income distribution experiences, on average, significant income losses that are more than 10 times larger than that of individuals between the 40th and 90th percentile of the distribution after a storm. Average losses following a hurricane are more than 4 times larger but point estimates are insignificant for the top decile group.

[9] This conclusion is supported by Cordoba & Uliczka (2021), who suggest that the 2005 Hurricane Katrina had a positive impact on the top 1% income share in Louisiana.

time lags, and their respective time weights correspond to $\dfrac{12 + (12 - m_{p,s})}{24}$ and $\dfrac{24 + (12 - m_{p,s})}{36}$, with $m_{p,s}$ as defined in (4.1).

Table 4.4 presents results from estimating equation (4.2) with two lags of the cyclone intensity measurement together with the cumulative impact through years, which is calculated by summing the coefficient of the contemporaneous cyclone variable and those of its lags.[10] Across all our income inequality measures except for the first quintile or the top 5% where the validity of the model is rejected, we do not find evidence of any intensification, nor attenuation of the impact beyond the year of the cyclone strike as none of the lags' point estimates are significant. This means that the immediate decrease in income inequality is stabilised in the short-run. This point is emphasised by the cumulative effect analysis: the sum of the coefficients is negative and significant after two years, with almost similar magnitude.

Table 4.4: System GMM regression of Gini index of income inequality on cyclone intensity, including additional lags.

	Bottom 60% share of aggregate income (1)	Bottom 40% share of aggregate income (2)	Gini index (3)	First quintile's share of aggregate income (4)	Fifth quintile's share of aggregate income (5)	Top 5% share of aggregate income (6)
$y_{c,t-1}$	0.119***	0.136***	0.085**	0.169***	0.063*	0.029
	(0.046)	(0.050)	(0.039)	(0.042)	(0.036)	(0.029)
$\overline{Cyc}_{c,t}$	0.009***	0.006***	-0.00009***	0.003***	-0.007**	0.004
	(0.002)	(0.001)	(0.00003)	(0.0008)	(0.003)	(0.004)
$\overline{Cyc}_{c,t-1}$	-0.0007	-0.0006	2.62e-06	-0.0007***	0.0002	-0.002
	(0.0009)	(0.0006)	(0.00001)	(0.0003)	(0.001)	(0.002)
$\overline{Cyc}_{c,t-2}$	-0.0002	-0.0002	5.36e-07	-0.0002	-0.00003	-0.001
	(0.0007)	(0.0004)	(0.00001)	(0.0002)	(0.001)	(0.001)
Observations	4255	4255	4255	4255	4255	4255
Number of counties	540	540	540	540	540	540
Number of instruments	93	93	93	93	93	93
Arellano-Bond test for AR(1) in first-differences	0.00	0.00	0.00	0.00	0.00	0.00
Arellano-Bond test for AR(2) in first-differences	0.73	0.25	0.43	0.07	0.35	0.51
Hansen test of overidentifying restrictions	0.14	0.16	0.30	0.00	0.12	0.05
Sum of all cyclone intensity coefficients	0.008***	0.005***	-0.00009**	0.002***	-0.007*	0.0006
	(0.003)	(0.002)	(0.00004)	(0.0009)	(0.004)	(0.005)

Notes: All regressions are two-step system GMM. Standard errors clustered by counties and incorporating the Windmeijer (2005) correction are in parentheses. Time fixed effects are included in all specifications, but not reported here.
Significance levels : *** 1% ; ** 5% ; * 10%.

Alternatively, by adding lags to the model, we also address the issue of how the frequency of events influences the results. Controlling for past experiences of tropical cyclones over the last two years leads to larger contemporaneous effects. This additional interpretation of the results offers thoughtful insights regarding counties' adaptive capacity. On the one hand, in accordance with Rubin & Segal (2015), as growth and income inequality are positively associated in the U.S., our results suggest that the larger effects on income inequality might be triggered by greater economic losses in counties where tropical cyclones occur frequently. In particular, as the income of top income groups is more sensitive to growth than that of lower income groups, the greater reduction in income inequality might be explained by greater income losses in top income groups. On the other hand, to limit the adverse effects on the poorest, counties that are repeatedly hit are more likely to implement disaster mitigating measures than their counterparts that are rarely affected. In the latter subgroup of counties, storm events may not constitute a sufficient base-level risk to implement specific disaster-related redistributive policies, or to undertake public investments

[10] In line with the distributed-lag literature, the immediate effect of tropical cyclones (*i.e.* the year that they occur, section 3) and the cumulated effect (with lag horizon $L > 0$) are separately estimated (Greene, 2003).

in risk mitigation (Schumacher & Strobl, 2011; Kousky, 2014). These stronger reductions in income inequality may also arise from the role of coordination and transfers between people, which increases in communities that are repeatedly exposed to storms (Zylberberg, 2010).[11]

4.3 Exploring transmission mechanisms

This last extension pertains to get a better understanding of the channels through which tropical cyclones lead to such redistribution of income. To do so, we quantify the effects of tropical cyclones on different components of aggregate income. It is well known that there is heterogeneity across households in terms of their primary sources of income. Even though most households derive their income from labour, low income groups mainly rely on transfer income while top income groups receive a larger portion of income from their wealth than others (Pleninger, 2022). As such, we distinctly analyse the effects on the logarithm of earnings, wage and salaries, capital income, which is defined here by the aggregate amount of interest, dividends or net rental income perceived by households, and other types of income. As explained in section 2, in this particular context, the aggregate amount of other types of income extracted from the ACS corresponds to a reasonable proxy for unemployment benefits. On top of this, we also investigate the effects on the share of employed population respectively below and above the national poverty level to help us discern the effects observed on labour income. Finally, a dynamic specification is rejected for these dependent variables, and thus, we use a standard panel fixed effects estimator.

Table 4.5 outlines the results of these regressions. Point estimates for aggregate earnings and wage or salary are statistically insignificant. However, the employment rate of population below national poverty threshold substantially decreases in the year a tropical cyclone occurs, while the employment rate for those above the poverty line is not significantly affected. This means that, even though the sample of individuals below poverty level does not exactly coincide with the two lowest quintiles of the aggregate income distribution, poorest individuals experience salary losses for after a storm shock. To explain the gains for the bottom quintiles in shares, our results provide support for a transfer payments channel as other sources of income - *i.e.* unemployment benefits - are positively affected by tropical cyclones (+0.1% increase for an additional km/h of tropical cyclone intensity, significant at the 1% level). Notwithstanding the fact that the amount of unemployment benefits does not outweight their lost wages, this compensation seems to be enough to increase the aggregate shares of bottom quintiles in comparison with higher groups of the distribution for which aggregate income shares is either unchanged or reduced. Finally, we find evidence of capital income losses in the wake of cyclone events: each additional km/h of wind speed intensity decreases the aggregate level of capital income by 0.2%. Most of these losses can arguably be attributed to the top quintile of the distribution. In fact, the share of capital income in total income is increasing for higher income groups, meaning that lowest income groups receive no capital income and middle income ones mainly rely on earnings but also derive a small share of their income from capital as they include small business owners (Pleninger, 2022). As tropical cyclones represent a major threat to physical capital, the losses for the top quintile in shares estimated above might be a consequence of the decrease in aggregate capital income that they mainly receive compared to other income groups. As for the top 5% of the distribution, it is likely that they experience larger capital losses than those with income between the 80th and 95th percentile. Yet, as their share of aggregate income is not affected by tropical cyclones, these losses might be compensated by other income sources or might not represent a significant share

[11] Within the same strand of the literature, Yamamura (2010) suggests that frequency of natural disasters fosters social capital in Japan.

of their total income.

These findings can also be linked with those presented in last subsection. As income inequality levels do not substantially rise back after the year of occurrence, the obtained results may be explained by the persistent increase in some income components such as transfer payments or social safety net programs observed in the aftermath of hurricanes in the U.S. (Deryugina, 2017). Indeed, the government's response to a catastrophe is not only limited to direct disaster aid programs, and non-disaster related transfers such as income maintenance payments, unemployment insurance and public medical benefits also increase due to the subsequent recession. This paper's baseline results stress a crucial role played by the two first quintiles in the estimated decrease in income inequality, and these two quintiles are precisely those benefitting the most from social benefits. They are also more likely to be in need after a cyclone strike (Fothergill & Peek, 2004). Results also suggest that the top quintile does not recover from its losses in aggregate income shares in the short-run, meaning that the replacement of destroyed capital takes more than two years to offset the losses in shares and be fully efficient.

Table 4.5: Results for regressing employment shares and income types on cyclone intensity

	Share of employed pop. below the poverty level (1)	Share of employed pop. above the poverty level (2)	Earnings (logged) (3)	Wage or salary income (logged) (4)	Interest, dividends or rental income (logged) (5)	Other sources of income (logged) (6)
$\overline{Cyc}_{c,t}$	-0.002**	0.003	0.00007	0.00006	-0.002**	0.001***
	(0.0008)	(0.002)	(0.00007)	(0.00007)	(0.001)	(0.0003)
Observations	5335	5335	5335	5335	5275	5335
Number of counties	540	540	540	540	540	540
Adjusted R^2	0.11	0.27	0.44	0.44	0.05	0.21

Notes: Panel fixed effects estimator. Robust standard errors clustered by counties are in parentheses. Time and county fixed effects are included, but not reported in the table. Significance levels : *** 1% ; ** 5% ; * 10%.

5 Conclusion

Recent debates have brought the impact of climate related disasters to the forefront of policy issues, either across or within countries. This paper tries to bring some fresh perspective on this topic and addresses the question of tropical cyclones' effects on income inequality in the U.S. Income inequality is an interesting variable to be analyzed as it is one of the most relevant variables to describe social justice. It is also arguably linked with economic growth or stability. In turn, this variable can impact health, education or social mobility. In the context of the U.S., poorest individuals are found to be more vulnerable to natural disasters than richer ones (Fothergill & Peek, 2004) and Belasen & Polachek (2009) show that hurricanes negatively affect employment rates. Income inequality might therefore be ultimately impacted, and providing a comprehensive study on how income distribution varies in the aftermath of catastrophe seems necessary. After having built a physical measure of tropical cyclone intensity which fits with a cross-county panel data framework, we show that such disasters decrease contemporaneous levels of local income inequality, though with low coefficients in magnitude. This finding is well in line with the already observed negative effects of hurricanes on counties' economic growth (Strobl, 2011), and the positive links between economic growth and income inequality in the U.S. (Rubin & Segal, 2015).

In a next step, we further examine the mechanisms that might explain this immediate effect. First, the two lowest quintiles and the top quintile of aggregate household income distribution appear to be those driving this result. Even though they derive a larger portion of their income from capital compared to lower income groups, the impact on the top 5% income share is insignificant. However, the impact is perhaps even different across higher income share levels, and focusing on the top 1% income share for instance can be of particular interest in our context (Cordoba & Uliczka, 2021). Unfortunately, we could not find the latter measurement in the ACS tables. Then, the investigation of timing effects indicates that the immediate effect seems to be persistent over time. The study of marginal cumulative effects concludes on an immediate impact that translates into an overall negative effect two years after the catastrophe. Hence, this result also documents the effects of tropical cyclones according to how past experiences of such disasters vary across counties. We find evidence of a larger decline in income inequality for those that are repeatedly hit. Counties with lower exposure to cyclonic risk may not find enough incentives to set automatic stabilisers operating in the aftermath of tropical cyclone events. These counties may have many other equally risky issues vying for their attention (Posner, 2006) compared to others where the occurrence of a natural disaster can represent a more focusing event, and thereby leading to more investments in mitigation or to altruist behaviours by political leaders (Kousky, 2014). Accordingly, local quality of governments and their capacity to react to natural disasters might also be determinant.

In a final extension brought to our main model, we try to quantify the impact of tropical cyclones on employment rates given poverty status as well as on various sources of aggregate income. The differential composition of households' income can be particularly relevant in explaining the distributional consequences of tropical cyclones on aggregate household income shares. While transfer income is a particularly important component of low income households, top income groups derive a greater share of total income from capital compared to other groups (Pleninger, 2022). We show that tropical cyclones negatively impact the poorest individuals' employment rate, but the underlying labour income losses are compensated by social insurance. In the meantime, the top quintile of the distribution experiences capital income depletion which explains, at least partly, its losses in aggregate shares. However, to better understand this income composition mechanism, further study on these extreme weather events' effects on distinct types of income specifically received by households with different levels of wealth seems warranted. One impediment to achieving this comes from the unavailability of transfer income distributions with respect to the standard of living.

Hence, our results somehow shed light on the efficiency of policy actions undertaken by governments, or other public institutions to counteract the adverse income effects on the poorest households. In fact, the persistent effect observed on our income inequality measures combined with such an income composition effect provide further support for Deryugina (2017) who demonstrates the crucial role of transfer payments in mitigating hurricane shocks. As suspected by Keerthiratne & Tol (2018), this depletion in income inequality levels might stem from the fact that poor individuals do not possess a high level of physical capital, and thus, losses can be disproportionate across the income distribution. Regarding this point, it would also be interesting to examine to what extent the substitution effect from physical capital to human capital due to natural disaster risk observed in Skidmore & Toya (2002) is reflected in our results. An insight to pursue this work would be to investigate how investments on physical capital and human capital fluctuate after a tropical cyclone, or how poverty rates are affected. Finally, the influence of internal migration in the aftermath of the catastrophe might constitute another key factor that explains our main result: Strobl (2011) shows that negative growth effects of hurricanes are partly due to the move of relatively richer people from affected counties in the wake of the hurricane. As only a reduced share of the U.S. economy is exposed to cyclonic risk, these phenomena may not have much of an impact on a more macro scale. Yet, it can be said that they play a role in shaping the income inequality trends across local areas.

Appendix of Chapter 4

A Alternative estimators

In this fourth chapter, we identify a negative causal link between tropical cyclones and income inequality in US counties. The analysis is based on a dynamic panel GMM approach, and in this appendix, the robustness of the results to the choice of alternative specifications is investigated. Table A.4.1 outlines the results obtained when "collapsing" the GMM instruments, when using a two-step difference GMM procedure, or a static panel fixed effects model.

Table A.4.1: Results for regressing income inequality on cyclone intensity: alternative estimators.

	Bottom 60% share of aggregate income (1)	Bottom 40% share of aggregate income (2)	Gini index (3)	First quintile's share of aggregate income (4)	Fifth quintile's share of aggregate income (5)	Top 5% share of aggregate income (6)
Two-step system GMM, using the "collapse" option						
$\overline{Cyc}_{c,t}$	0.006***	0.004***	-0.00006***	0.001***	-0.005**	-0.001
	(0.001)	(0.001)	(0.00002)	(0.0004)	(0.002)	(0.002)
Observations	4795	4795	4795	4795	4795	4795
Number of counties	540	540	540	540	540	540
Number of instruments	28	28	28	28	28	28
Arellano-Bond test for AR(1) in first-differences	0.00	0.00	0.00	0.00	0.00	0.00
Arellano-Bond test for AR(2) in first-differences	0.41	0.72	0.80	0.40	0.77	0.36
Hansen test of overidentifying restrictions	0.05	0.34	0.36	0.41	0.26	0.08
Two-step difference GMM						
$\overline{Cyc}_{c,t}$	0.005***	0.004***	-0.00006***	0.001***	-0.004**	0.001
	(0.001)	(0.001)	(0.00002)	(0.0004)	(0.002)	(0.003)
Observations	4255	4255	4255	4255	4255	4255
Number of counties	540	540	540	540	540	540
Number of instruments	39	39	39	39	39	39
Arellano-Bond test for AR(1) in first-differences	0.00	0.00	0.00	0.00	0.00	0.00
Arellano-Bond test for AR(2) in first-differences	0.88	0.81	0.53	0.85	0.37	0.41
Hansen test of overidentifying restrictions	0.27	0.63	0.45	0.65	0.33	0.25
Static panel data model: fixed effects estimator						
$\overline{Cyc}_{c,t}$	0.003***	0.002***	-0.00003*	0.001***	-0.003	0.001
	(0.001)	(0.0008)	(0.00002)	(0.0004)	(0.002)	(0.002)
Observations	5335	5335	5335	5335	5335	5335
Number of counties	540	540	540	540	540	540
Adjusted R^2	0.04	0.03	0.05	0.03	0.05	0.05

Notes: Standard errors clustered by counties are in parentheses. For the panel fixed effects estimator, we compute robust standard errors. For the difference and system GMM, standard errors incorporate the Windmeijer (2005) correction. Time fixed effects are included in all specifications, but not reported in the table.
Significance levels : *** 1% ; ** 5% ; * 10%.

On top of this, one more class of model (static) can be explored, that is fractional outcome models. Indeed, all along this chapter, our outcome variables are lying between zero and one, meaning that the dependent variable is limited. Two cases arise when outcome variables are bounded by 0 and 1: either one knows the denominator, either one does not. Fractional outcome models have to be used in the latter case, for example, when the dependent variable is an index of pollution levels, patient oxygen saturation, Gini index or any proportion.

We distinguish two types of fractional outcome models, namely, fractional response regression and beta regression. These models are appropriate when one has a dependent variable that takes values within the $[0; 1]$ set. If the dependent variable takes values in the open set $]0;1[$, then beta regression is more recommended. Both of these models focus on the mean of a dependent variable Y conditional on covariates X, denoted μ_X.

Fractional response regressions are fitted on continuous zero to one data using probit, logit or heteroskedastic probit. These models are analogous to the binary logit or probit models, and only differ according to the fact that the y variable can take on continuous values within the unit interval. Fractional response regressions are estimated using quasi-likelihood methods, which approximate the true density function f_0 used in maximum likelihood estimations by a function f chosen using partial knowledge of the true distribution f_0. For instance, Papke & Wooldridge (1996) use Bernoulli quasi-likelihood methods. Beta regressions are used when the dependent variable excludes 0 and 1 values and is assumed to follow a beta distribution. In fact, following a beta distribution implies that 0 and 1 values are taken on with probability zero. As it is assumed that the true distribution is the beta distribution, estimations are made with maximum likelihood methods.

Fractional outcome models all use *link functions*. The link function ensures that $\mu_X \in]0;1[$. More specifically, if we denote $g(.)$ the link function, we have:

$$g(E[Y|X]) = g(\mu_X) = X\beta$$

$$\iff \mu_X = g^{-1}(X\beta)$$

In the context of beta regressions, several link functions exist. Among others, we identify:

$$g(\mu_X) = \begin{cases} ln(\mu_X/(1-\mu_X)) & \text{logit link} \\ \Phi^{-1}(\mu_X) & \text{probit link} \\ ln(-ln(1-\mu_X)) & \text{cloglog link} \\ -ln(-ln(\mu_X)) & \text{loglog link} \end{cases}$$

We also introduce a parameter $\psi_X > 0$ that scales the conditional variance according to:

$$V(Y|X) = \mu_X(1-\mu_X)/(1+\psi_X)$$

And, its associated scale link function, $h(\psi_X) = X\gamma$, which is linking this parameter to the covariates X:

$$h(\psi_X) = \begin{cases} ln(\psi_X) & \text{log} \\ \sqrt{\psi_X} & \text{root} \\ \psi_X & \text{identity} \end{cases}$$

In the end, the distribution of Y is approximated by a beta distribution function as follows:

$$f(Y;\mu_X;\psi_X) = \frac{\Gamma(\psi_X)}{\Gamma(\mu_X\psi_X)\Gamma((1-\mu_X)\psi_X)} Y^{\mu_X\psi_X - 1}(1-Y)^{(1-\mu_X)\psi_X - 1}$$

With $\Gamma(z) = \int_0^{+\infty} t^{z-1}e^{-t}dt$ the gamma function.

Beta regressions were first introduced by Ferrari & Cribari-Neto (2004), and then, enhanced by Smithson & Verkuilen (2006) to allow the scale parameter to depend on the set of covariates. As explained above, this estimation strategy seems to be more appropriated to the present framework, *i.e.* the effect of tropical cyclones on income inequality in the US. We focus on the Gini index as in Castellani, Pattitoni, & Scorcu (2012), who use beta regression to estimate Gini index values for the prices of art given artists' popularity (Artist Price Heterogeneity). Finally, for the sake of space, we opt for the default scale link function, which is the log function. The choice of other functions does not affect the results.

Table A.4.2: Beta regression results, the effect of tropical cyclones on Gini coefficient

	Logit link (1)	Probit link (2)	Cloglog link (3)	Loglog link (4)
$\overline{Cyc}_{i,t}$	-0.00014*	-0.00009**	-0.00011**	-0.00010*
	(0.00007)	(0.00004)	(0.00005)	(0.00005)
Observations	5335	5335	5335	5335
BIC	-23740.2	-23740.3	-23738.4	-23741.7
Marginal effects	-0.00003*	-0.00003*	-0.00003*	-0.00003*
	(0.00002)	(0.00002)	(0.00002)	(0.00002)

Notes: Beta regression estimates. Robust standard errors are in parentheses. Time and country fixed effects are included in all estimations, but not reported in the table. All estimations use a log scale link function based on the cyclone intensity measurement.
Significance levels : *** 1 % ; ** 5 % ; * 10 %.

Table A.4.2 presents the estimates obtained for different choices of link function. As suggested by Smithson & Verkuilen (2006), we select the model that minimizes the Bayesian information criterion (BIC), which helps in selecting the correct model in large samples. Here, according to this criterion, the loglog function is the correct specification and the marginal effect is similar to the one obtained with a static fixed effects model, with a significance slightly above the 5% level. Across all specifications, point estimates are negative and significant, and provide further support to the conclusion made in this chapter.

B Alternative cyclone metrics

Table B.4.1: Results for regressing income inequality on cyclone intensity: alternative cyclone metrics.

	Bottom 60% share of aggregate income (1)	Bottom 40% share of aggregate income (2)	Gini index (3)	First quintile's share of aggregate income (4)	Fifth quintile's share of aggregate income (5)	Top 5% share of aggregate income (6)
% Population exposed$_{c,t}$	0.150***	0.106***	-0.002***	0.038***	-0.158**	-0.028
	(0.048)	(0.032)	(0.001)	(0.015)	(0.070)	(0.082)
Observations	4795	4795	4795	4795	4795	4795
Number of counties	540	540	540	540	540	540
Number of instruments	57	57	57	57	57	57
Arellano-Bond test for AR(1) in first-differences	0.00	0.00	0.00	0.00	0.00	0.00
Arellano-Bond test for AR(2) in first-differences	0.89	0.97	0.38	0.29	0.37	0.34
Hansen test of overidentifying restrictions	0.42	0.74	0.27	0.51	0.09	0.02
$\overline{Cyc}_{c,t}$ without monthly weight	0.002***	0.002***	-0.00002**	0.0006***	-0.002*	0.0004
	(0.0006)	(0.0004)	(9.61e-06)	(0.0002)	(0.0009)	(0.001)
Observations	4795	4795	4795	4795	4795	4795
Number of counties	540	540	540	540	540	540
Number of instruments	57	57	57	57	57	57
Arellano-Bond test for AR(1) in first-differences	0.00	0.00	0.00	0.00	0.00	0.00
Arellano-Bond test for AR(2) in first-differences	0.72	0.94	0.50	0.33	0.48	0.39
Hansen test of overidentifying restrictions	0.69	0.90	0.50	0.68	0.23	0.10
$\overline{Wind}_{c,t}$	0.002***	0.001***	-0.00002**	0.0004***	-0.001	0.0009
	(0.0005)	(0.0003)	(7.79e-06)	(0.0001)	(0.0007)	(0.0008)
Observations	4795	4795	4795	4795	4795	4795
Number of counties	540	540	540	540	540	540
Number of instruments	57	57	57	57	57	57
Arellano-Bond test for AR(1) in first-differences	0.00	0.00	0.00	0.00	0.00	0.00
Arellano-Bond test for AR(2) in first-differences	0.54	0.81	0.63	0.43	0.58	0.47
Hansen test of overidentifying restrictions	0.51	0.81	0.57	0.41	0.24	0.33

Notes: All regressions are two-step system GMM. Standard errors clustered by counties and incorporating the Windmeijer (2005) correction are in parentheses. Time fixed effects are included in all specifications, but not reported in the table.
Significance levels : *** 1% ; ** 5% ; * 10%.

C Additional controls

In these complementary estimations, a distinction is made between meteorological controls and economic controls. Meteorological controls refer to the average annual temperatures (measured in °Celsius), and total annual precipitation levels (measured in mm). Data were obtained from the *Climatic Research Unit gridded Time Series* database (CRU TS v4.05; Harris & al., 2020), which provides monthly estimates derived from land-based weather station observations for the period 1901 to 2019. However, CRU TS data are recorded at 0.5° latitude x 0.5° longitude resolution, which makes us unable to match them to all the sample counties. For the same reasons as those listed for our cyclone intensity measurement, these local climatic variables are considered as not strictly exogenous in the estimation. Then, economic controls correspond to income per capita growth (measured in constant 2019 dollars) and the logarithm of the share of poor households. These data come from the ACS (1-year estimates) and are plausibly endogenous. Accordingly, we use these control variables' lagged values. Households with total income in the last 12 months below an appropriate poverty threshold are classified as poor, and poverty threshold are defined as in section 2.

Table C.4.1: Results for regressing income inequality on cyclone intensity: additional controls.

	Bottom 60% share of aggregate income (1)	Bottom 40% share of aggregate income (2)	Gini index (3)	First quintile's share of aggregate income (4)	Fifth quintile's share of aggregate income (5)	Top 5% share of aggregate income (6)
Meteorological controls						
$\overline{Cyc}_{c,t}$	0.005**	0.003**	-0.00006*	0.0009	-0.005	0.001
	(0.002)	(0.001)	(0.001)	(0.0006)	(0.003)	(0.004)
$Precipitation_{c,t}$	-0.0002	-0.0001	2.91e-06	0.00005	0.0002	0.00003
	(0.0002)	(0.0001)	(3.66e-06)	(0.020)	(0.0003)	(0.004)
$\overline{Temp}_{c,t}$	-0.085***	-0.042**	0.001***	-0.015*	0.158***	0.125***
	(0.031)	(0.019)	(0.0004)	(0.008)	(0.040)	(0.036)
Observations	1975	1975	1975	1975	1975	1975
Number of counties	223	223	223	223	223	223
Number of instruments	48	48	48	48	48	48
Arellano-Bond test for AR(1) in first-differences	0.00	0.00	0.00	0.00	0.00	0.00
Arellano-Bond test for AR(2) in first-differences	0.82	0.62	0.82	0.59	0.66	0.65
Hansen test of overidentifying restrictions	0.28	0.44	0.70	0.56	0.74	0.82
Economic controls						
$\overline{Cyc}_{c,t}$	0.005***	0.003**	-0.00007**	0.0008	-0.006**	-0.002
	(0.002)	(0.001)	(0.00003)	(0.0006)	(0.003)	(0.003)
$\Delta ln(income\ per\ capita)_{c,t}$	-0.811	-0.386	0.016*	-0.009	1.886**	2.102**
	(0.572)	(0.298)	(0.009)	(0.126)	(0.855)	(1.040)
$ln(share\ of\ poor\ households)_{c,t}$	-0.048	0.007	0.002	0.065	0.203	0.151
	(0.251)	(0.159)	(0.004)	(0.075)	(0.340)	(0.394)
Observations	4255	4255	4255	4255	4255	4255
Number of counties	540	540	540	540	540	540
Number of instruments	44	44	44	44	44	44
Arellano-Bond test for AR(1) in first-differences	0.00	0.00	0.00	0.00	0.00	0.00
Arellano-Bond test for AR(2) in first-differences	0.30	0.71	0.95	0.67	0.68	0.25
Hansen test of overidentifying restrictions	0.46	0.84	0.17	0.30	0.07	0.01

Notes: Both regressions are two-step system GMM with collapsed instruments. Standard errors clustered by counties and incorporating the Windmeijer (2005) correction are in parentheses. Time fixed effects are included in all specifications, but not reported in the table.

Significance levels : *** 1% ; ** 5% ; * 10%.

D Alternative samples

Table D.4.1: Results for regressing income inequality on cyclone intensity: alternative samples.

	Bottom 60% share of aggregate income (1)	Bottom 40% share of aggregate income (2)	Gini index (3)	First quintile's share of aggregate income (4)	Fifth quintile's share of aggregate income (5)	Top 5% share of aggregate income (6)
Balanced panel						
$\overline{Cyc}_{c,t}$	0.007***	0.004***	-0.00008***	0.001***	-0.007***	-0.002
	(0.002)	(0.001)	(0.00002)	(0.0004)	(0.002)	(0.003)
Observations	4743	4743	4743	4743	4743	4743
Number of counties	527	527	527	527	527	527
Number of instruments	57	57	57	57	57	57
Arellano-Bond test for AR(1) in first-differences	0.00	0.00	0.00	0.00	0.00	0.00
Arellano-Bond test for AR(2) in first-differences	0.99	0.44	0.49	0.18	0.56	0.37
Hansen test of overidentifying restrictions	0.24	0.44	0.31	0.28	0.11	0.06
Panel extended to all counties ever affected between 1950 and 2019						
$\overline{Cyc}_{c,t}$	0.006***	0.004***	-0.00006***	0.001***	-0.005**	-0.0003
	(0.002)	(0.0009)	(0.00002)	(0.0004)	(0.002)	(0.002)
Observations	5571	5571	5571	5571	5571	5571
Number of counties	627	627	627	627	627	627
Number of instruments	57	57	57	57	57	57
Arellano-Bond test for AR(1) in first-differences	0.00	0.00	0.00	0.00	0.00	0.00
Arellano-Bond test for AR(2) in first-differences	0.83	0.91	0.46	0.40	0.51	0.39
Hansen test of overidentifying restrictions	0.24	0.63	0.25	0.37	0.08	0.06
Panel extended to all U.S. counties						
$\overline{Cyc}_{c,t}$	0.004***	0.003***	-0.00005**	0.001**	-0.003	0.001
	(0.001)	(0.001)	(0.00002)	(0.0005)	(0.002)	(0.002)
Observations	7328	7328	7328	7328	7328	7328
Number of counties	827	827	827	827	827	827
Number of instruments	57	57	57	57	57	57
Arellano-Bond test for AR(1) in first-differences	0.00	0.00	0.00	0.00	0.00	0.00
Arellano-Bond test for AR(2) in first-differences	0.22	0.63	0.65	0.24	0.34	0.82
Hansen test of overidentifying restrictions	0.12	0.35	0.52	0.17	0.17	0.04

Notes: All regressions are two-step system GMM. Standard errors clustered by counties and incorporating the Windmeijer (2005) correction are in parentheses. Time fixed effects are included in all specifications, but not reported in the table.
Significance levels : *** 1% ; ** 5% ; * 10%.

General conclusion

Written in French

Cette thèse de doctorat examine la question de l'impact économique des cyclones tropicaux, qui correspond à un volet de la littérature sur les catastrophes naturelles, elle-même inscrite au sein de la plus large catégorie des catastrophes macroéconomiques rares définie par Barro & Ursúa (2012). Cette problématique est traitée suivant un plan thématico-géographique. L'analyse des effets causaux sur la croissance économique et sur les inégalités de revenus est effectuée à différentes échelles en utilisant diverses méthodes économétriques.

Le premier article s'appuie sur un modèle de régression pondérée. Les valeurs extrêmes prises par la variable dépendante sont sous-pondérées du fait que celles-ci sont vraisemblablement dues à des facteurs économiques externes et indépendants comme la forte hausse du produit intérieur brut (PIB) irlandais en 2015, qui s'explique en grande partie par la relocalisation d'actifs immatériels – recherche et développement, logiciels etc. – par de grandes multinationales. Autre exemple, la chute du taux de croissance au Yémen en 2015 est sans doute davantage due au commencement des conflits infranationaux plutôt qu'à son exposition aux cyclones tropicaux cette année-là. Cette méthode de régression linéaire robuste aux valeurs extrêmes est notamment utilisée par Krichene & al. (2021) afin de démontrer l'impact négatif des cyclones tropicaux sur la croissance économique à l'échelle mondiale.

En scindant notre échantillon initial entre petits états insulaires en développement (PEID) et le reste des territoires mondiaux, nous obtenons ici des résultats originaux, à savoir un effet négatif et persistant sur les PEID et une absence d'effet sur l'échantillon complémentaire des non PEID. Ces effets se maintiennent durant les 15 années qui suivent l'occurrence d'un choc cyclonique. Le nombre de retards à inclure dans le modèle est fixé en considérant ce qui est effectué par ailleurs dans la littérature empirique sur le sujet (Felbermayr & Gröschl, 2014 ; Hsiang & Jina, 2014 ; Krichene & al. 2021). Afin d'étudier les effets à plus long terme, nous proposons dans une extension au chapitre 2 une analyse des effets permanents sur la croissance économique à l'aide d'un modèle à retards distribués géométriquement. L'hypothèse d'une distribution géométrique des coefficients retardés permet d'obtenir une convergence de ces coefficients à horizon infini. Les résultats supplémentaires ainsi obtenus laissent entrevoir le fait que la tendance observée sur 15 ans reste inchangée à plus long terme. Autrement dit, les effets négatifs contemporains dans les PEID ne sont probablement jamais compensés.

Dans le chapitre 3, nous nous intéressons de plus près aux corrélations spatiales entre les groupes qui constituent notre échantillon. L'importance des effets spatio-temporels est notamment mise en exergue par Lind (2019) dans le contexte de l'influence des conditions météorologiques sur les résultats d'élections en Norvège. Les modèles d'économétrie spatiale utilisés dans ce chapitre consistent à inclure une variable dite « spatialement retardée » comme variable explicative dans l'équation d'intérêt ou à contrôler l'autocorrélation spatiale dans le terme d'erreur. Nos résultats montrent que l'occurrence d'un cyclone dans un territoire contigu n'influe pas sur la croissance économique du territoire étudié. En revanche, les dynamiques économiques des territoires voisins ainsi que leurs termes d'erreurs révèlent être déterminants à l'échelle des comtés. A l'échelle des états, nos tests de spécification suggèrent de prendre en compte uniquement l'autocorrélation spatiale dans les erreurs. Ces méthodes nous permettent de réfuter tout impact significatif sur la croissance économique des comtés ou des états américains lorsque ceux-ci sont échantillonnés à travers le pays. En revanche, des analyses portant spécifiquement sur l'Etat de Floride montrent des pertes significatives de croissance à la fois au sein des comtés floridiens, mais également à l'échelle de cet Etat en général à l'aide de méthodes de modélisation de séries temporelles.

Enfin, dans le but d'estimer l'impact des cyclones tropicaux sur les inégalités aux Etats-Unis, nous exploitons un panel doté d'une courte dimension temporelle mais d'un nombre de comtés important. Ces caractéristiques, couplées au fait de supposer que les indicateurs d'inégalités s'expliquent en partie par leur valeur retardée, conduisent à tirer profit de la méthode des moments généralisés (MMG) en système. Cette méthode économétrique, principalement destinée aux modélisations dynamiques, consiste à définir des instruments dits « internes » aux variables explicatives, c'est-à-dire leurs valeurs retardées. La MMG en système est composé de deux équations, une correspondant à l'équation d'intérêt en première différence et la seconde étant celle en niveau, instrumentées respectivement par des variables en niveau et en première différence. L'une des particularités de cette méthode est de pouvoir revenir sur le postulat d'exogénéité *stricto sensu* de notre indicateur. Jusqu'à présent, nous avons considéré notre mesure d'intensité cyclonique comme purement exogène, ce qui est discutable à plusieurs égards. En effet, malgré la promptitude et l'imprévisibilité d'un épisode cyclonique discutée dans l'introduction générale, la fréquence ou l'intensité des phénomènes peuvent être, quant à elles, liées à des inobservables tels que les pratiques culturelles et économiques locales (Bui & al., 2014), ou le changement climatique anthropique (GIEC, 2022). A ce titre, la MMG en système offre la possibilité de considérer le choc cyclonique comme exogène vis-à-vis de la période en cours, mais pouvant tout de même être influencée par les perturbations passées. Cette stratégie permet d'estimer des effets bénéfiques des cyclones tropicaux sur les inégalités de revenus. Cet impact s'explique, pour partie, par une diminution des revenus du capital pour le cinquième quintile de la distribution des revenus agrégés, et par une compensation des pertes de revenus du travail par les allocations relatives au chômage pour les deux premiers quintiles de la distribution.

Ces diverses méthodologies ont été mises à contribution dans le cadre d'évaluations *ex-post*. Or, l'anticipation des effets des catastrophes naturelles représente un enjeu majeur pour les économistes. Ceci correspond à la suite des travaux prévus, et résultant directement de cette thèse de doctorat. La plupart des analyses *ex-ante* sur notre thématique s'effectuent par le biais de modèles théoriques. Tout d'abord, on retrouve des modèles s'appuyant sur la théorie de la croissance néoclassique. A la suite du choc sur les facteurs de production que sont le travail et le capital, et compte tenu de rendements d'échelle constants, ces modèles prédisent un retour progressif à l'état stationnaire de l'économie défini en l'absence de la catastrophe. Dans notre premier chapitre, nous démontrons la conformité des prédictions de cette théorie avec l'incidence des chocs cycloniques dans les PEID entre 1970 et 2015. Ensuite, il existe des modèles théoriques considérant le progrès technologique - et donc la productivité - comme endogène. Cuaresma (2010) souligne la pertinence de ces modèles en démontrant l'existence d'un effet de substitution entre capital physique et capital humain au lendemain d'une catastrophe naturelle. L'accumulation du capital humain compense les pertes matérielles en augmentant la productivité des agents d'une économie à travers l'apprentissage. Ces différentes théories sont toutefois critiquées pour ne pas tenir compte des caractéristiques géographiques (Krugman, 2011), qui sont prépondérantes en économie de l'environnement. Ainsi, Botzen & al. (2019) recommandent l'utilisation de modèles économiques régionaux, c'est-à-dire de modèles faisant le lien entre les impacts macroéconomiques indirects et les pertes directes observables à l'échelle microéconomique.

En pratique, ces modèles théoriques prennent principalement la forme de tableaux d'entrées-sorties (TES), de modèles d'équilibre général calculable (MEGC), ou encore des modèles d'évaluation intégrée (*Integrated Assessment Models* ; IAM). Les TES ainsi que les MEGC s'appuient sur des matrices de comptabilité sociale. Les TES visent à estimer les effets d'équilibre sectoriels et les répercutions en termes d'échanges commerciaux. Entre autres, ils permettent de détecter les secteurs vulnérables aux catastrophes naturelles. Les MEGC offrent davantage de flexibilité que les TES dans le sens où ceux-ci intègrent la volatilité de l'offre et de demande et permettent de définir des relations non-linéaires entre la production et ses intrants. En ce sens, les MEGC sont plus fiables que les TES en ce qui concerne les projections à long-terme. Enfin, les IAM sont des modèles qui intègrent le changement climatique, et ont pour objectif de déterminer le coût social du carbone, ou encore la trajectoire économique optimale en vue d'une diminution d'émission de gaz à effet de serre.

Pour conclure, il convient de souligner qu'à l'instar de tout travail de recherche, les résultats présentés dans cette thèse soulèvent autant de questions qu'elles n'apportent de réponses. Par exemple, on peut s'interroger sur la dépendance de la causalité avec la manière de quantifier les coûts dans les études. Dans le cas des biens matériels, faut-il considérer la valeur pré-catastrophe de ces biens, ou bien les coûts nécessaires à leur reconstruction ? Changer de composition dans la nature des coûts permettrait-il de remettre en question le statut des résultats établis jusqu'à présent ? Cette thèse introduit également des problématiques nouvelles. Elle ouvre notamment la voie à une étude explorant les liens entre catastrophes naturelles et politiques fiscales à travers un modèle théorique. En effet, le chapitre 2 montre l'incapacité des PEID à investir au lendemain d'un épisode cyclonique, et laisse penser que les contraintes d'endettement constituent un élément d'explication à cet obstacle rencontré par les pouvoirs publics. Le chapitre 4 nous éclaire quant à lui sur l'influence des transferts sociaux dans la correction des inégalités de revenus. De manière générale, les catastrophes naturelles entraînent des conséquences fiscales importantes. Si un Etat peut financer sa reconstruction en augmentant les dépenses publiques ou en réduisant les recettes fiscales, il peut également se relancer par des politiques d'austérité dans l'éventualité où sa marge de manœuvre budgétaire serait ténue.

En utilisant un modèle d'équilibre général dynamique stochastique, et plus particulièrement un modèle néo-keynésien à agents hétérogènes, l'objectif serait d'évaluer l'optimalité d'une politique fiscale contrainte d'arbitrer entre un investissement dans l'adaptation aux chocs, définie par une atténuation du choc négatif sur la productivité de l'entreprise, et maintien de la demande à travers des subventions aux agents, ce qui se caractériserait par une augmentation de l'utilité. Ce type de modèle permet de prendre en compte des phénomènes essentiels tels que l'épargne de précaution face à un risque idiosyncratique - non-assurable - représenté par la catastrophe naturelle. Cela permettrait également d'obtenir des estimations sur les effets utilitaires des catastrophes, et donc, des résultats en termes de bien-être. Un équilibre dit de « *no-trade* » se manifesterait alors du fait de la rigidité dans les prix et les salaires, des marchés incomplets et des frictions en termes de recherche et appariement sur le marché du travail (Krusell, Mukoyama & Smith, 2011 ; Ravn & Sterk, 2017). Une partie empirique devrait être intégrée et fera très certainement appel à d'un modèle vectoriel auto-régressif avec composante exogène (VARX). Elle décrirait le comportement des différentes séries statistiques et les fonctions de réponse obtenues en simulant le choc exogène. Les données économiques nécessaires à l'étude peuvent être extraites des *World Development Indicators* (Banque Mondiale). L'idéal serait de développer la partie théorique en utilisant un modèle calibré sur la base des résultats obtenus empiriquement, et pourquoi pas, de proposer des résultats *ex-ante* face au changement climatique. Le développement du modèle théorique est en cours.

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General Appendix

A Interview with Sylvie Malardel and Hélène Vérèmes (Météo-France/University of Reunion Island - LACy)

A series of questions has been asked to two researchers in Physics upon my understanding of cyclone phenomena: pertinence of my indicator of exposure, differences between classes of cyclones, etc. The discussion was in French and took place on November 17, 2021.

1) ***What is the difference between tropical cyclones and extratropical cyclones ?***

Several characteristics differ between these two phenomena. Tropical cyclones correspond to vertical swirling winds, forming around depression zones in tropical regions' oceans or seas. Water corresponds to their main source of energy and its temperature must be above 26°C. Tropical cyclones' winds lose strength as they gain altitude. In contrast, extratropical cyclones move forward thanks to meteorological dynamics and can generate strong winds in altitude. Extratropical cyclones basically refer to bad weathers found in extratropical regions, *i.e.* between 30° and 60° latitude. Above this threshold of latitude, we talk about polar cyclones.

In this thesis, the *Tropical Cyclone Exposure Database* (TCE-DAT; Geiger & al., 2018) is exploited. It extracts 2713 landfalling cyclones with at least 34 knots ($\approx$ 63 km/h) wind speed and sustained at least one minute from the widely used *International Best Track Archive for Climate Stewardship* (IBTrACS; Knapp & al., 2010). Initially, IBTrACS records all tropical cyclone events from all available Regional Specialized Meteorological Centers (RSMCs) and other agencies around the world. Sources are the following ones:

- Australian Bureau of Meteorology (BoM) (as TCWC Perth, Darwin, Brisbane)
- Fiji Meteorological Service (as RSMC Nadi)
- India Meteorological Department (as RSMC New Delhi)
- Japan Meteorological Agency (as RSMC Tokyo)
- Météo-France (as RSMC La Reunion)
- Meteorological Service of New Zealand, Ltd. (as TCWC Wellington)
- U.S. National Oceanic and Atmospheric Administration's (NOAA's) Central Pacific Hurricane Center (as RSMC Honolulu)
- NOAA's National Hurricane Center (NHC, as RSMC Miami)

- China Meteorological Administration's Shanghai Typhoon Institute (CMA/STI)
- Hong Kong Observatory (HKO)
- U.S. Department of Defense Joint Typhoon Warning Center (JTWC)
- C. Neumann's Southern Hemisphere data (Neumann 1999)

In TCE-DAT, recorded events also affect countries located outside tropical cyclone basins. These countries are therefore hit by extratropical cyclones, which were initially tropical cyclone events. Tropical cyclones can progress through oceans and seas to become extratropical cyclones. By doing this, they change their physical structure.

Moreover, tropical cyclone events are recorded in the database if they have lasted at least one minute with a mean wind speed of 34 knots during this time interval. This corresponds to an American convention. Other meteorological centers use 5 minutes or 10 minutes.

2) ***Why is tropical cyclone intensity lowered when making landfall?***

As stated above, tropical cyclones need water sources to be formed. If there is no water, then tropical cyclones automatically lose their main source of energy. This loss of energy is also due to frictions and surface roughness when making landfall. If a tropical cyclone passes through a land and finds water again, it can regenerate and regain strength. One weakness of TCE-DAT is the lack of concern regarding areas' topography.

3) ***What do you think about my cyclone indicator?***

Instead of choosing the maximum wind speed for each pixel during a year, it could have been pertinent to take the sum of all wind speed records, and then normalizing with the total exposed area. However, this may not match with the purpose of the study, as a 34 knots wind speed is not likely to cause any damage to infrastructures.

This issue regarding frequency is salient. Indeed, after a storm, soils can be water-saturated and infrastructures can be weakened, which can be deteriorated even more by another cyclone, even if the latter is less powerful. Accumulation of cyclones can be detrimental for economies.

4) ***What do you think about the control variables included in my first article's preferred specification? Any other ideas?***

The cyclone measurement is controlled by temperature and precipitation. Temperature seems to be less essential than precipitation. Nevertheless, arguments can be found in favour of its inclusion. In fact, Météo France states: *"Une température de surface de l'océan plus élevée ne « facilite » en effet pas forcément la naissance de cyclones. Mais un cyclone déjà bien formé « puisera » bien plus d'énergie pour se renforcer dans une atmosphère humidifiée au-dessus d'océans réchauffés. En effet, la capacité de l'atmosphère à contenir de l'humidité augmente avec sa température. Ce supplément d'humidité sera à l'origine d'un renforcement des pluies cycloniques qui elles-mêmes intensifient le système."* [1]

Beyond these two meteorological covariates, storm surges and swells should be of greater importance. Cyclonic swells can come from far away and can bring persistent waves on coastal areas. These waves can subsist for days. Storm surges have quick onset, but generally do not last long. Impacts of both surges and swells can be devastating (*e.g.* Hurricane Katrina) and the extent of damages depends on the coastal area's topography, or tide levels. However, it is difficult to get cross-country data on these two phenomena as they are often captured by local stations.

[1] `https://meteofrance.com/le-changement-climatique/observer-le-changement-climatique/cyclones-et-changement-climatique`