Schlussbericht
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Ökonomie des Klimawandels

„Globale Erwärmung, Naturkatastrophen und ökonomische Konsequenzen - DisasterEcon“

Projektlaufzeit:
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1.1. Aufgabenstellung

Mit dem Förderschwerpunkt „Ökonomie des Klimawandels“ verfolgt das Bundesministerium für Bildung und Forschung das Ziel „belastbare und praktikable Ansätze zur Abschätzung und Kommunikation der Kosten, Risiken und Chancen kohlenstoffarmer Wachstums- und Entwicklungsmodelle“ zu erforschen, da diese „sich als wesentlich für die Bereitschaft von Regierungen, Unternehmen und Bürgern erweisen, Vorsorgemaßnahmen zu ergreifen und zu finanzieren.“ Große Bedeutung erhält hierbei die „Bereitstellung von empirisch fundiertem und handlungsorientiertem Wissen“. Nach Ansicht des Bundeministeriums für Bildung und Forschung gibt es im Bereich der ökonomischen Betrachtung des Klimawandels deutliche Lücken. Diese Lücken umfassen unter anderem ökonomische Abschätzungen zu den „Kosten und Risiken des Klimawandels […] - insbesondere auch in langfristigen Szenarienrechnungen.“[1]

Vor diesem Hintergrund befasst sich das Projekt DisasterEcon mit den ökonomischen Konsequenzen von klimainduzierten Naturkatstrophen – einer in der Ökonomie bisher selten betrachteten Konsequenz des Klimawandels. Viele empirische Untersuchungen deuten darauf hin, dass der Klimawandel die Wahrscheinlichkeit des Eintretens und/oder die Schwere von bestimmten Naturkatastrophentypen beeinflusst (vgl. SREX, 2012). So wird z.B. im fünften IPCC-Bericht berichtet, dass das Risiko für klimawandelindizierte Naturkatastrophen wie Hitzewellen, Starkregen und Überschwemmungen von Küstengebieten momentan moderat (mit hoher Wahrscheinlichkeit), aber bei einem Anstieg der globalen Temperatur um 1°C als hoch (mit mittlerer Wahrscheinlichkeit) eingeschätzt wird. Da Naturkatastrophen erhebliche Auswirkungen auf Ökologie und Ökonomie haben (vgl. IPCC, 2014), wird ein fortschreitender Anstieg der globalen Temperatur zu weiteren Kosten führen. Diese zusätzlichen – durch Naturkatastrophen – erzeugten Kosten des Klimawandels auf das ökonomische System, wurden im Projekt DisasterEcon untersucht. Der Fokus des Projekts liegt dabei auf den Aspekten der wirtschaftlichen Entwicklung und der subjektiven Lebenszufriedenheit. Ziel des Projekts ist es herauszufinden, ob klimainduzierte Naturkatastrophen langfristige Wachstumseffekte haben, wie stark diese sind und über welche Transmissionskanäle sich diese manifestieren. Darüber hinaus stellt sich die Frage, ob die, aus der erhöhten Wahrscheinlichkeit

[1]Vgl. Bekanntmachung des Bundesministeriums für Forschung und Entwicklung vom 29.04.2010, abrufbar unter: https://www.fona.de/de/10429 (Stand 12.10.2015).

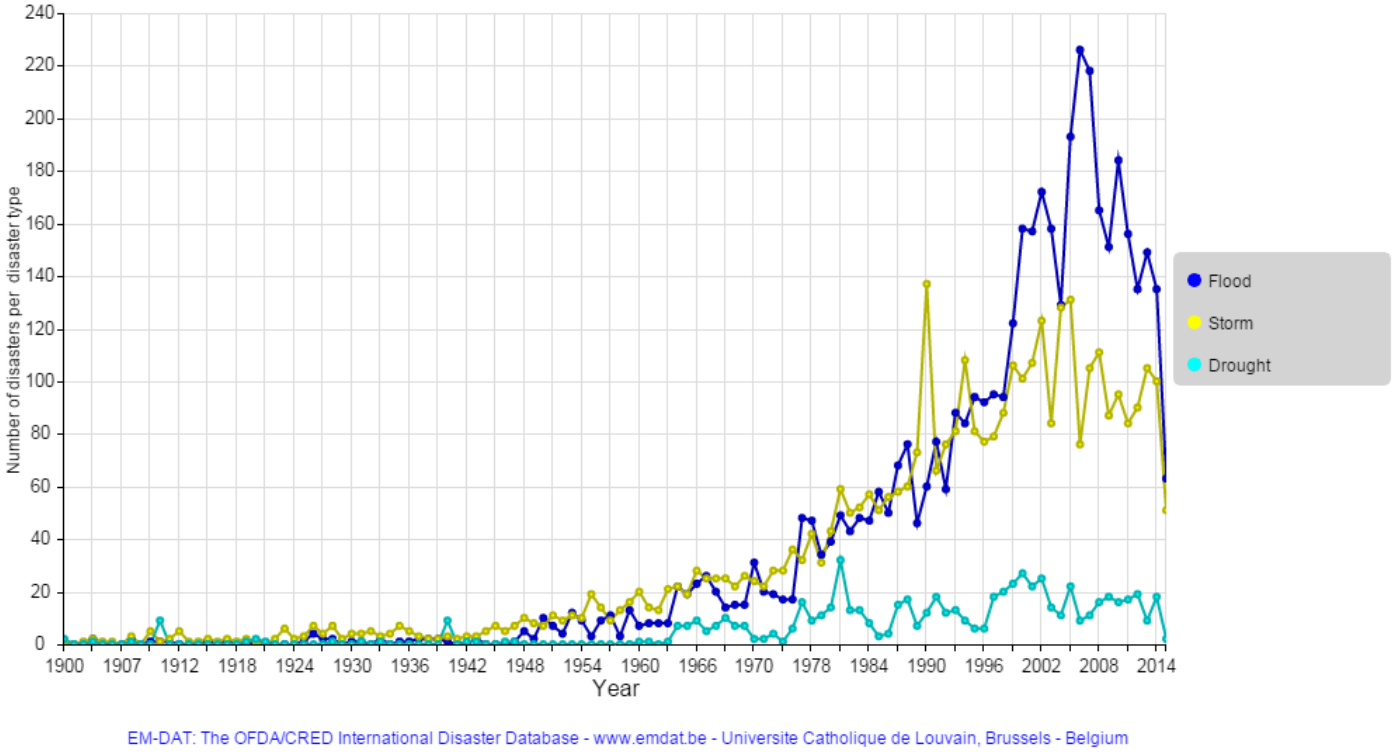
des Auftretens bzw. der größeren Schwere solcher Katastrophen, die Lebenszufriedenheit der potenziell betroffenen Menschen abnimmt.

1.2. Ausgangslage und Voraussetzungen

Naturkatastrophen haben von jeher die Menschheit bedroht und das menschliche Zusammenleben beeinflusst. In den letzten Jahrzehnten kam es immer wieder zu Naturkatastrophen von immensem Ausmaß. Dabei zählen das Erdbeben in Haiti aus dem Jahr 2008 und der erdbebenbedingte Tsunami aus dem Jahr 2002, mit jeweils ca. 220.000 Todesopfern, zu den tödlichsten Naturkatastrophen der letzten 35 Jahre (Munich Re, 2015a). Aber auch offensichtlich klimainduzierte Naturkatastrophen können erhebliche Auswirkungen haben. So zählen die zwei tropischen Stürme im indischen Ozean aus dem Jahr 2008 und 1991, mit jeweils ca. 140.000 Todesopfern, ebenfalls zu den tödlichsten Naturkatastrophen der letzten Jahrzehnte. Nicht überraschend finden sich in der Kategorie tödlichste Naturkatstrophen vor allem Entwicklungsländer. Betrachtet man hingegen die durch Naturkatastrophen hervorgerufenen monetären Schäden, so ändert sich das Bild. Die drei schadensreichsten Katastrophen der letzten 35 Jahre waren der Tsunami in Japan (2011) mit 210 Milliarden US$, Hurrikan Katarina (2005) mit 125 Milliarden US$ und das Kobe-Erdbeben (1991) mit 100 Milliarden US$ (Munich Re, 2015b). Erwartungsgemäß wird diese Kategorie von entwickelten Ländern dominiert. Allerdings wird deutlich, dass alle Länder, unabhängig von ihrem Entwicklungsstand, unter den Konsequenzen von Naturkatastrophen leiden. Es stellt sich somit die Frage, wie sich diese Entwicklung in Zukunft fortsetzen wird.

Tatsächlich hat die Häufigkeit des Eintretens von Naturkatastrophen im Zeitablauf zugenommen. Dies lässt sich anhand einer sehr oft zitierten Datenbank zu Naturkatastrophen, der EM-DAT Datenbank, die von Wissenschaftler der *Université Catholique de Louvain* am *Centre for Research on the Epidemiology of Disasters* (CRED) erstellt und gepflegt wird, dokumentieren. EM-DAT umfasst Daten zu Häufigkeit und Auswirkungen von Naturkatastrophen weltweit, über einen Zeitraum von 1900 bis heute. Insgesamt beinhaltet die Datenbank über 18.000 Katastrophen. Basierend auf den EM-DAT Daten lässt sich ein positiver Trend in der Häufigkeit von klimainduzierten Naturkatastrophen beobachten (vgl. Abbildung 1). Dabei ist allerdings zu beachten, dass die Datenbank erst ab ca. 1970 einen weltweiten Coverage hat, und der Anstieg der Häufigkeiten zuvor teilweise auf eine umfassendere Erfassung zurück zu führen ist.

Abbildung 1: Jährliche Anzahl von ausgewählten Naturkatastrophentypen 1900 – 2014



Seit 1900 stieg die durchschnittliche Oberflächentemperatur der Erde um ca. 0.7 – 0.8 °C (NASA, 2015). Seit dem 4. Sachstandsbericht des IPCC (2007) gilt es in der Wissenschaft als grundsätzlich akzeptiert, dass ein Teil der Erwärmung auf menschliche Aktivitäten zurückzuführen ist (Vgl. IPCC, 2007 & 2014). Dies lässt sich z.B. durch die Konzentration an Treibhausgasen in der Atmosphäre belegen. So stieg die Konzentration von Kohlendioxid (CO_2) von 280 ppm (parts per million) im Jahr 1850 auf das heutige Level von knapp 400 ppm. Da die Wirkung der erhöhten Konzentration von Treibhausgasen in der Atmosphäre langfristig ist, ist damit zu rechnen, dass sich auch bei einer massiven Reduktion der Treibhausgasemissionen sich der Prozess der globalen Erwärmung zunächst einmal fortsetzt (siehe auch Solomon et.al, 2009).

In der Wissenschaft wird eine Vielzahl von möglichen Konsequenzen des globalen Temperaturanstiegs diskutiert. Diese umfassen unter anderem den Anstieg des Meeresspiegels (Cazenave und Nerem, 2004), eine Reduktion an Biodiversität (IPCC, 2014) eine Ausbreitung an Krankheiten wie Malaria und allgemein negative Folgen auf die Gesundheit (Patz et al., 2005). Wie aus mehreren Studien hervorgeht, hat der Anstieg der globalen Temperatur auch signifikante Auswirkungen auf die Häufigkeit, Dauer und Intensität extremer Wetterereignisse wie Dürren, Überflutungen, Stürme und Hitzewellen (vgl. z.B. Milly et al., 2002; Anderson und Bausch, 2005, Hoyos et al., 2006; van Aalst, 2006). In Anbetracht dieser Erkenntnisse stellt sich die Frage, welche

mittel- und langfristigen Wachstumseffekte der Klimawandel durch seinen Einfluss auf Naturkatastrophen hat.

Die ökonomische Literatur hat erst vor wenigen Jahren damit begonnen, sich diesem Thema systematisch zuzuwenden. Die Pionierstudie von Skidmore und Toya (2002) ist hierbei ein wichtiger Meilenstein. Der Großteil der ökonomischen Studien, die in der Folgezeit entstanden sind, nutzt zur Untersuchung der ökonomischen Effekten von Naturkatstrophen die oben beschriebene EM-DAT Datenbank. Betrachtet man allerdings die Regeln, unter denen Naturkatastrophen in der Datenbank erfasst werden, so fällt auf, dass ein Kriterium für die Aufnahme einer Naturkatastrophe in die Datenbank, der entstandene monetäre Schaden ist. Dies kann zum einen dazu führen, dass einige Naturkatastrophen nicht in die Datenbank aufgenommen werden. Gleichzeitig entsteht per Definition eine Korrelation zwischen der Häufigkeit von Naturkatastrophen in EM-DAT und der wirtschaftlichen Entwicklung. Dieser Sachverhalt kann dazu führen, dass in Wachstumsregressionen, dem typischerweise verwendeten empirischen Verfahren zum Nachweis von Wachstumseffekten, ein massives Endogenitätsproblem auftritt. Endogenität führt dazu, dass Schätzergebnisse verzerrt und inkonsistent sind. Um dieses Problem zu vermeiden, müssen z.B. ausgesprochen komplexe empirische Methoden verwendet werden. Eine Alternative hierzu. ist die Verwendung echt exogener Katastrophendaten. Im vorliegenden Projekt wurde der zweite Weg gewählt und rein physikalisch/meteorologische Indikatoren zur Messung der Häufigkeit und Intensität von Naturkatastrophen verwendet. Der Wissenstand zu Beginn des Projekts wird im Folgenden zusammengefasst.

Die vorhandenen theoretischen Modelle basieren weitestgehend auf deterministischen Versionen des sogenannten neoklassischen Wachstumsmodells. Dieses zeichnet sich dadurch aus, dass Sparentscheidungen und technologischer Fortschritt exogen sind. Wird der langfristige Effekt von Naturkatastrophen auf das Wirtschaftswachstum in diesem Rahmen modelliert, so lässt sich kein Effekt finden (Okuyama, 2003). Allerdings ist die Annahme, dass Naturkatastrophen keinen Einfluss auf individuelles Sparverhalten, den technischen Fortschritt, das Humankapital und die Fertilität haben, unter Umständen unrealistisch (Loayza et al., 2009). Fortgeschrittene Wachstumsmodelle endogenisieren daher viele dieser Faktoren. Lecocq und Shalizi (2007) argumentieren, dass Naturkatastrophen sich negativ auf Bildungsinvestitionen auswirken und somit das langfristige Wirtschaftswachstum negativ beeinflussen. Jang, Huh und Wong (2008) schlussfolgern aus ihrem Modell, dass Investitionen in physisches Kapital (d.h. die Sparquote) je geringer ausfallen, desto höher die Wahrscheinlichkeit einer Naturkatastrophe. Ist der Anstieg in der Wahrscheinlichkeit des Eintritts einer Naturkatstrophe permanent, so ergibt sich ein Effekt auf das langfristige

Wirtschaftswachstum durch eine dauerhaft geringere Sparquote. All diese theoretischen Überlegungen deuten an, dass es einen langfristigen Zusammenhang zwischen der Häufigkeit von Naturkatastrophen und dem Wirtschaftswachstum geben kann. Letztendlich muss die Frage, ob Naturkatastrophen langfristige Wachstumseffekte aufweisen, allerdings empirisch geklärt werden.

Die zu Projektbeginn vorhandenen empirischen Studien befassen sich hauptsächlich mit dem Effekt von Naturkatastrophen auf das kurzfristige Wirtschaftswachstum. Ein Großteil dieser Studien findet einen negativen Effekt von Naturkatastrophen auf das Wirtschaftswachstum im Folgejahr (Rasmussen, 2004; Heger, Julca und Paddison, 2008; Raddatz, 2007). Der Effekt variiert in Abhängigkeit des Naturkatastrophentyps und des Entwicklungsstands der betroffenen Länder (Noy, 2009 und Fomby et al., 2009). So finden Fomby et al. (2009) für Überflutungen einen positiven und für Dürren, Erdbeben und Stürme einen negativen Wachstumseffekt im Folgejahr.

Die langfristigen Folgen von Naturkatastrophen waren zu Projektbeginn empirisch kaum untersucht und bei den wenigen vorhandenen Studien ergibt sich ein uneinheitliches Gesamtbild. Während einige Autoren negative Effekte finden (Vgl. Loayza et al., 2009; Cuaresma, Hlouskova und Obersteiner, 2008), finden andere einen positiven Effekt (Vgl. Skidmore und Toya, 2002; Jaramillo, 2007). Die Effekte unterscheiden sich jedoch in der Art der Naturkatastrophe (Skidmore und Toya, 2002; Jaramillo, 2007) und dem Entwicklungsstand der betroffenen Länder (Cuaresma, Hlouskova und Obersteiner, 2008). Alle genannten Studien nutzen EM-DAT Daten, um die Häufigkeit von Naturkatastrophen zu messen und weisen damit das schon erwähnte potentielle Endogenitätsproblem auf.

Fast überhaupt keine Evidenz gab es zu Projektbeginn zu möglichen Kanälen durch die Naturkatastrophen das langfristige Wirtschaftswachstum beeinflussen. Loayza et al. (2009) schreiben, dass technischer Fortschritt und die relative Ausstattung an physischem und Humankapital mögliche Transmissionskanäle darstellen können. Lecocq und Shalizi (2007) argumentieren, dass Naturkatastrophen einen negativen langfristigen Effekt auf das Wirtschaftswachstum durch ihren Einfluss auf F&E und Humankapital haben.

Die bisher angeführten Studien messen die ökonomischen Auswirkungen von Naturkatastrophen in Veränderungen des Bruttoinlandsprodukts. Hierbei fungiert das Bruttoinlandsprodukt als Maß für die Wohlfahrt eines Landes. Diese Methode ist gängig in der Ökonomie und wird auch bei der Untersuchung der langfristigen Effekte von Naturkatastrophen im Projekt DisasterEcon verwendet. Allerdings ist es möglich, dass Naturkatastrophen zusätzliche Wohlfahrtseffekte haben, die sich nicht

im Bruttoinlandsprodukt widerspiegeln. In Anbetracht der traumatischen Erfahrung, die mit dem Erleben einer Naturkatastrophe einhergeht, bietet sich die subjektive Lebenszufriedenheit als geeignetes Maß an. Zu Beginn des Projekts war die Studie von Luechinger und Raschky (2009) eine der wenigen existierenden Studien auf diesem Gebiet. Die Autoren untersuchten die Veränderung der subjektiven Lebenszufriedenheit in Gebieten, die von Überflutungen betroffen waren und fanden einen kurzfristigen negativen Effekt.

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1.3. Planung und Ablauf des Vorhabens

Das Projekt hat im November 2011 mit einer systematischen Analyse der vorhandenen themarelevanten Literatur und einem „Start-Up-Workshop“ begonnen. Der Workshop wurde am Institut für Weltwirtschaft in Kiel ausgerichtet und diente dazu, Gemeinsamkeiten zu weiteren Projekten aus dem Förderschwerpunkt zu identifizieren und ein geeignetes Diskussionsforum zu entwickeln. Ausführungen zur weiteren Zusammenarbeit mit anderen Stellen finden sich in Kapitel 1.4.

Das Projekt gliedert sich in vier Teilprojekte.[2] Grundlegend für die Bearbeitung aller Teilprojekte war zunächst eine ausführliche Recherche und Lektüre der themenrelevanten Literatur, die in eine Literaturübersicht mündete. Diese Arbeiten wurden im Juni 2012 formell abgeschlossen, aber ständig aktualisiert. Im weiteren Zeitverlauf wurde an den einzelnen Teilprojekten parallel gearbeitet. Im Folgenden werden Planung und Verlauf der einzelnen Projekte separat beschrieben.

Das erste Teilprojekt beschäftigte sich mit den theoretischen Grundlagen; hier insbesondere der Wachstumstheorie. Es wurden hierzu theoretische Modelle gesichtet und studiert, wie sich Naturkatastrophen innerhalb dieser Modelle auf den Wachstumspfad von Volkswirtschaften auswirken. Dieses erste Teilprojekt stellte die Grundlage für alle anderen Teilprojekte dar, da die beiden empirischen und auch das experimentelle Teilprojekt auf den wachstumstheoretischen Grundlagen aufbauen. Die Ergebnisse dieses Teilprojekts flossen somit wesentlich in die

[2] Eine genaue Beschreibung der Teilprojekte und dessen Ergebnisse finden sich in Kapitel 2.1.

Forschungspapiere ein, die aus den anderen drei Teilprojekten entstandenen sind. Das Teilprojekt wurde somit erfolgreich abgeschlossen.

Das zweite Teilprojekt befasst sich mit der empirischen Untersuchung der langfristigen Effekte von Naturkatastrophen auf das Wirtschaftswachstum und der Identifikation von Wirkungskanälen. Mit Hilfe von statistischen Verfahren wurde hier überprüft, ob Naturkatastrophen das langfristige Wirtschaftswachstum beeinflussen und falls ja, durch welche Transmissionskanäle dies geschieht. Entscheidend für die empirische Analyse war die Erstellung einer umfassenden Datenbank. Diese sollte neben sozio-ökonomischen Informationen zu einer Vielzahl von Ländern speziell konstruierte Schwere- und Häufigkeitsindikatoren für einzelne Naturkatastrophentypen enthalten. Der Aufbau der Datenbank konnte wie geplant gegen Ende 2012 erfolgreich abgeschlossen werden. Auch hier wurden bei Bedarf im Projektverlauf noch Aktualisierungen vorgenommen. Mit Beginn des Jahres 2013 wurde die empirische Analyse für einzelne Naturkatastrophentypen begonnen. Im Verlauf des Jahres konnten erste Ergebnisse zu den langfristigen Effekten von tropischen Stürmen und Dürren auf das Wirtschaftswachstum erzielt werden. Im Verlauf des Jahres 2014 entstanden aus den Forschungsergebnissen erste Diskussionspapiere, die in der Folge auf Workshops und Konferenzen vorgetragen und in der Folge weiter verbessert wurden. Ein Forschungspapier zu Dürren wurde bereits bei der Fachzeitschrift „Economics Bulletin“ eingereicht und nach einem Revise & Resubmit noch einmal überarbeitet und wiedereingereicht (vgl. Anhang zu diesem Bericht). Ein weiteres Forschungspapier zu den Wachstumseffekten von tropischen Stürmen wurde ebenfalls fertig gestellt und nach einigen Hinweisen auf Konferenzen noch einmal überarbeitet. Es soll Ende dieses Jahres ebenfalls bei einer internationalen Fachzeitschrift zur Publikation eingereicht werden (auch dieses Papier findet sich im Anhang). Das Teilprojekt ist insofern erfolgreich abgeschlossen. Es ist allerdings geplant, auf diesem Gebiet unter Verwendung der aufgebauten Datenbank und einigen zusätzlichen Erweiterungen noch weitere Forschungspapiere zu erstellen. Mindestens zwei weitere Papiere zu Dürren und Extremniederschlägen sind bereits in Arbeit.

Im dritten Teilprojekt standen die Transmissionskanäle von Naturkatastrophen im Zentrum der Betrachtung. Da hierzu die Datenlage regelmäßig sehr schlecht ist, war im dritten Teilprojekt zunächst eine rein experimentelle Untersuchung geplant. Die Entwicklung eines geeigneten experimentellen Designs für das geplante Laborexperiment erwies sich in der Praxis als sehr viel schwieriger als ursprünglich gedacht. Der zunächst geplante Ablauf des Experiments zeigte sich in einigen Probeläufen als deutlich zu komplex. Zudem war es ausgesprochen schwierig, in dem ursprünglich geplanten Design eine Auszahlungsstruktur zu finden, in der unterschiedliche Strategien der Teilnehmer auch zu deutlich unterschiedlichen Auszahlungen führten. Nach Beratung mit

Fachleuten aus dem Projektteam und einschlägigen Fachkollegen, wurde das grundlegende Design des Experiments noch einmal deutlich verändert, so dass alle nachfolgenden Arbeitsschritte wiederholt werden mussten. Die Rückmeldung aus Vorträgen auf Workshops hatte zudem ergeben, dass die externe Validität der Ergebnisse des Experiments erheblich gesteigert werden könnte, wenn man das Experiment nicht nur mit Studenten, sondern mit nach demographischen Kriterien zusammengestellten Teilnehmern durchführen würde. Dies ließ sich allerdings wegen des überschaubar großen Subject-Pools von Experimental-Laboren an Universitäten zunächst nicht realisieren. Als eine ausgezeichnete Alternative stellte sich heraus, das Experiment mit einem interaktiven Fragebogen über ein Meinungsforschungsinstitut zu organisieren. Der Vorteil dieser Vorgehensweise besteht darin, dass einerseits auf das sehr umfangreiche Sample von Meinungsforschungsinstituten zurückgegriffen werden kann und dabei auch demographische Kriterien herangezogen werden können. Zudem war die Durchführung des Experiments hier in relativ kurzer Zeit möglich, was vor dem Hintergrund des nahenden Projektendes ein wichtiger Faktor war. Um diese Möglichkeit wahrzunehmen, wurde ein kostenneutraler Verlängerungsantrag um ein halbes Jahr gestellt, der auch bewilligt wurde. Im Anschluss wurde mit der Firma IPSOS eine Kooperation vereinbart und das Experiment gemeinsam geplant. Bis zum Jahresende 2014 konnten die notwendigen Programmierarbeiten abgeschlossen werden. Nach einigen Testläufen konnte das Experiment dann im Frühjahr 2015 durchgeführt werden. Derzeit läuft noch die Auswertung der Ergebnisse der Experimente, die aber zügig voranschreitet und auch bereits ein recht eindeutiges Bild ergeben hat. Derzeit werden die Ergebnisse in einem Forschungspapier zusammengestellt. Das Teilprojekt ist somit weitgehend abgeschlossen.

Darüber hinaus wurde das dritte Teilprojekt kostenneutral noch um eine wichtige Untersuchung erweitert. Beim Aufbau der Datenbank zu Teilprojekt 2 stellte sich heraus, dass eine Verbindung von Naturkatastrophendaten und Daten des Sozioökonomischen Panels eine Analyse des Sparverhaltens von Betroffenen der Jahrhundertflut vom August 2002 in Sachsen ermöglichte. Somit konnte hier, anders als ursprünglich gedacht, auch eine empirische Analyse auf der Basis von Sekundärdaten durchgeführt werden. Seit Beginn des Jahres 2013 wurde an dem hierzu nötigen Datensatz gearbeitet. Gegen Ende 2013 konnten erste Ergebnisse erzielt und auf Fachkonferenzen und Workshops präsentiert werden. Ein Jahr später war die Untersuchung dann soweit fortgeschritten, dass die Ergebnisse in einem Forschungspapier niedergeschrieben werden konnten, das bereits bei einer internationalen Fachzeitschrift zur Publikation eingereicht wurde (auch dieses Papier ist dem Bericht angefügt).

Das vierte Teilprojekt, welches sich mit dem Einfluss von Naturkatastrophenrisiko auf empfundenes Glück und Lebenszufriedenheit beschäftigt, konnte ebenfalls erfolgreich und termingerecht abgeschlossen werden. Zunächst wurde auch hier ein geeigneter Datensatz zusammengestellt, auf dessen Basis dann die empirische Untersuchung stattfinden konnte. Diese wurde bereits im Jahr 2013 abgeschlossen und die Ergebnisse in einem weiteren Forschungspapier niedergelegt. Das Papier wurde auf verschiedenen Konferenzen vorgetragen und als Ergebnis hiervon noch einmal wesentlich erweitert. Inzwischen wurde auch dieses Papier bei einer Fachzeitschrift eingereicht (Ecological Economics) und hat derzeit den Status „Revise and Resubmit“. Die anregten Änderungen werden derzeit eingearbeitet und das Papier dann wieder eingereicht. Die aktuelle Fassung dieses Papiers findet sich ebenfalls im Anhang zu diesem Bericht.

1.4. Anknüpfung an den wissenschaftlichen Stand

Bei der Planung und Durchführung des Projekts wurde stets darauf geachtet, die bereits vorliegende Literatur angemessen in den eigenen Arbeiten zu berücksichtigen. So begann jeder Arbeitsschritt mit einer sorgfältigen Aufarbeitung der einschlägigen Literatur; zudem wurden auch während des Projekts neu publizierte Arbeiten eingearbeitet. Alle Forschungsergebnisse wurden nicht nur auf Workshops innerhalb des Netzwerkes, sondern auch in Forschungskolloquien anderer Universitäten und auf internationalen Fachtagungen vorgetragen und diskutiert. Die hierbei entstandenen Anregungen wurden in die bereits vorliegenden Publikationen eingearbeitet. Alle Publikationen sind oder werden zudem bei referierten Fachzeitschriften eingereicht. Das Refereeverfahren dieser Zeitschriften stellt letztendlich noch einmal sicher, dass die Arbeiten dem wissenschaftlichen Stand der Literatur genügen.

1.5. Zusammenarbeit mit anderen Stellen

Im Rahmen des Projekts wurde intensiv mit Kooperationspartnern, aber auch mit anderen Mitgliedern des Förderschwerpunkts zusammen gearbeitet. Kurz nach Projektbeginn wurden bei einem „Start-Up-Workshop“ am Institut für Weltwirtschaft in Kiel erste Kontakte zu weiteren Projekten geknüpft. Insbesondere der Kontakt zu den Projekten EXPECT (Kiel), CliP (Dresden), Accept (Kiel), EnergyEFFAIR (Berlin/Göttingen) war über den gesamten Projektzeitraum intensiv. Weitere Workshops wurden im Januar 2013 an der Helmut-Schmidt Universität in Hamburg und im Januar 2014 am ifo Dresden durchgeführt. Auf den Workshops wurden erste Ergebnisse vorgestellt und ausgiebig diskutiert. Wichtige Hinweise zur Verbesserung der vorgestellten Forschungsarbeiten konnten so in die weitere Bearbeitung mit einfließen. Des Weiteren kam es bei einem internationalen Workshop zu "Climate Shocks and Household Behavior" im Dezember 2013 am DIW Berlin zu einem Austausch mit dem Projekt Shocks Mongolia (DIW Berlin).

Neben der selbstorganisierten Zusammenarbeit mit den oben genannten Projekten, wurde im Verlauf des Projekts die Zusammenarbeit einzelner Themenschwerpunkte innerhalb des Förderschwerpunkts von Seiten des BMBF angeregt und intensiviert. Auftakt für die angestrebte Bündelung einzelner Projekte in Themenschwerpunkte war die 1. Statuskonferenz zur Ökonomie des Klimawandels im Juni 2013 in Bonn. Das Projekt DisasterEcon hat sich in den Themenschwerpunkt A „Kosten von Klimawandel, Klimaschutz und Anpassung an den Klimawandel“ eingeordnet. Bei dem ersten Workshop des Themenschwerpunkts A im November 2013 am Hamburgischen WeltWirtschaftsInstitut (HWWI) wurden erste Ergebnisse der einzelnen Projektmitglieder ausgetauscht und damit begonnen, einen gemeinsamen Standpunkt zu zentralen Fragen finden. Die Zusammenarbeit und Koordination des Themenschwerpunktes wurde im folgenden Jahr bei Workshops im Mai und September in Berlin fortgesetzt. Die Zusammenarbeit im Themenschwerpunkt mündete in einem Hintergrundpapier zu den Kosten des Klimawandels und einem Austausch mit Stakeholdern beim 1. Forum Klimaökonomie im März 2015 in Berlin. Die Ergebnisse des Projekts DisasterEcon wurden bei der abschließenden 2. Statuskonferenz Anfang November 2015 in Berlin präsentiert und mit den anwesenden Stakeholdern ausgiebig diskutiert.

Die Zusammenarbeit zum Thema Klimaökonomik mit anderen Forschern innerhalb des Netzwerkes, aber auch darüber hinaus war aus Sicht des Antragstellers so vielversprechend, dass aus dem Projekt weitergehende Forschungsaktivitäten entstanden sind. So hat sich z.B. gezeigt, dass eine Untersuchung der durch Klimawandel und Naturkatastrophen ausgelösten Migrationsbewegungen ein sehr interessantes und eng verwandtes Forschungsfeld darstellt. In Zusammenarbeit mit Dr. Max Steinhardt (Helmut-Schmidt-Universität Hamburg) wird der Antragsteller im Juli 2016 einen vom CESifo Netzwerk finanzierten Workshop zum Thema „Climate Change and Migration“ in Venedig durchführen, in den Vorarbeiten aus dem Projekt eingehen werden.

2. Projektergebnisse und Projektnutzen

2.1. Projektergebnisse

Die Projektergebnisse werden im Folgenden chronologisch in der Reihenfolge der vier Teilprojekte dargestellt.

Das erste Teilprojekt befasste sich mit der theoretischen Fundierung langfristiger Wachstumskonsequenzen von klimabedingten Naturkatastrophen. Als Grundlage für die

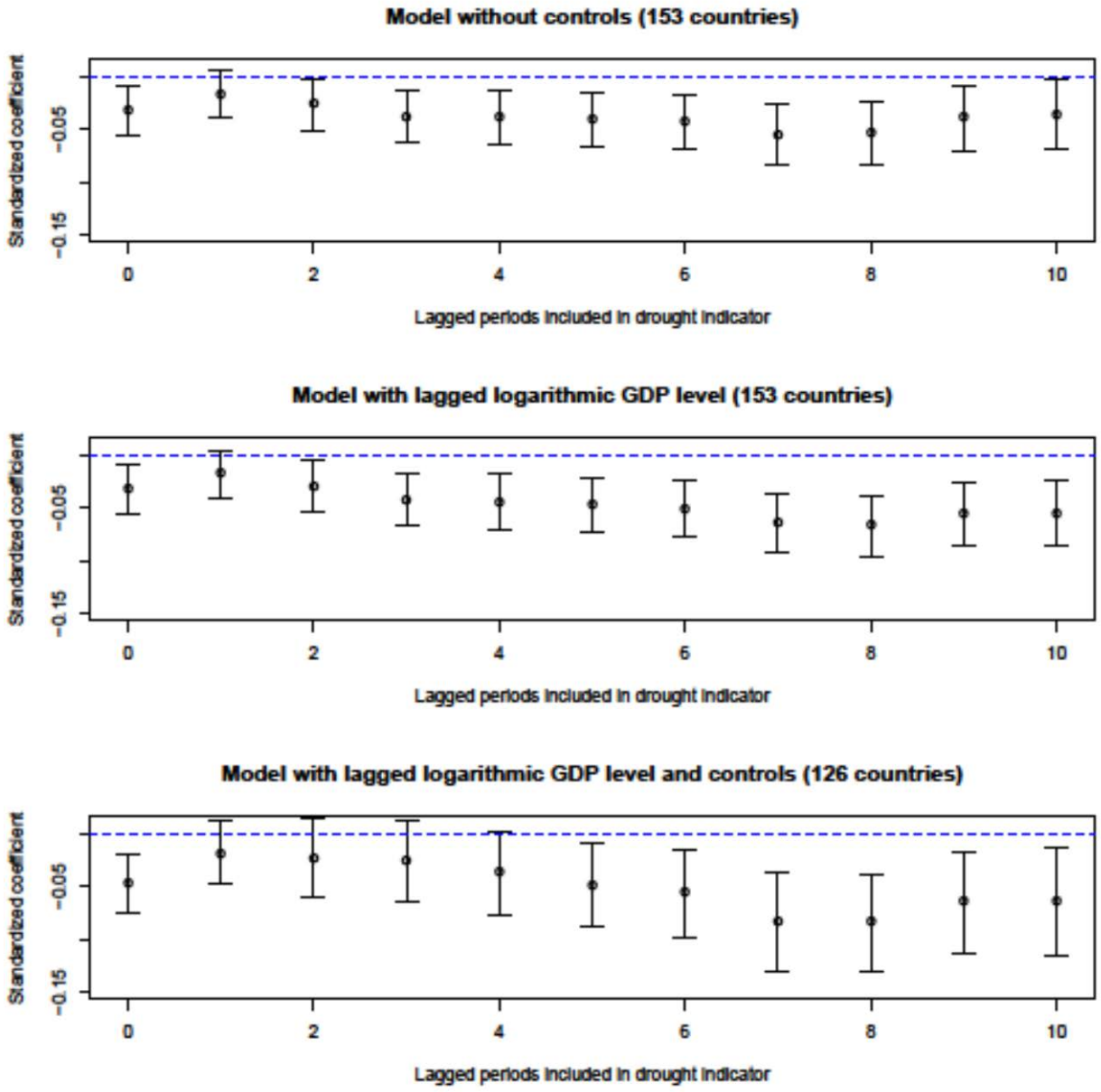
theoretische Analyse dienten dabei verschiedene Wachstumsmodelle, in denen die Wirkung von Naturkatastrophen studiert wurde. In Ihrer Reinform liefern die meisten Wachstumsmodelle das Ergebnis, dass Naturkatastrophen nur kurzfristige, aber keine langfristigen Wachstumseffekte haben. Dies gilt sowohl für neoklassische als auch für endogene Wachstumsmodelle. Die Analyse zeigte allerdings, dass im endogenen Wachstumsmodell von Lucas und Uzawa (vgl. Uzawa, 1965, Lucas, 1988), in dem Haushalte ihren Nutzen durch Konsum maximieren, langfristige Wachstumseffekte auftreten können. In dieser Modellwelt können Haushalte ihren intertemporalen Konsum erhöhen, indem sie ihre vorhandenen Ressourcen in die Akkumulation von physischen und/oder von Humankapital (z.B. Bildung) investieren. Durch Optimierung der Investitionsentscheidung ergibt sich eine optimale Aufteilung der Ressourcen zwischen Human- und physischen Kapital, die durch Naturkatastrophen beeinflusst werden kann. Dabei hängt die Wirkung davon ab, ob Naturkatastrophen eher das Leben oder eher den Kapitalstock bedrohen. Die Analyse hat zudem aufgezeigt, dass langfristige Wachstumseffekte in beinahe allen Wachstumsmodellen resultieren, wenn zentrale Verhaltensparameter, wie z.B. die Sparquote, die Fertilität oder die Humankapitalbildung durch Naturkatastrophen beeinflusst werden. Ob dies der Fall ist und welche Kanäle hier in der Praxis eine Rolle spielen, ist eine empirische Frage, die in den Teilprojekten II und III untersucht wurde. Die theoretischen Ergebnisse gingen maßgeblich in die empirischen Schätzmodelle des Teilprojekt II sowie das experimentelle Design in Teilprojekt III ein.

In Teilprojekt II wurde untersucht, ob Naturkatastrophen tatsächlich langfristige Wachstumseffekte aufweisen. Hierzu wurde zunächst eine umfangreiche Datenbank angelegt, die für eine große Zahl von Ländern und möglichst viele Jahre makroökonomische Rahmendaten beinhaltet. Darüber hinaus wurden in diese Datenbank Naturkatastrophendaten eingefügt. Wegen des oben beschriebenen Endogenitätsproblems wurden hier keine EM-DAT Daten verwendet, sondern Daten aus physikalischen und meteorologischen Datenbanken.

In einem ersten Forschungsansatz wurde analysiert, welchen Einfluss Dürren auf das Wirtschaftswachstum haben. Dürren wurden dabei über einen Regenfallindikator identifiziert. Basierend auf einem Sample von 153 Ländern über den Zeitraum von 1960 bis 2002 zeigt sich, dass Dürren tatsächlich für die betroffenen Länder negative langfristige Wachstumskonsequenzen haben (vgl. Abbildung 2). Die Ergebnisse sind dabei robust im Hinblick auf die Verwendung alternativer Schätzverfahren. Weiterhin zeigt sich, dass die negativen Wachstumskonsequenzen zwar prinzipiell sowohl in entwickelten wie in unterentwickelten Ländern auftreten, jedoch in letzteren numerisch wesentlich bedeutender sind. Dies dürfte vor allem darauf zurück zu führen sein, dass sich arme Länder sehr viel schlechter gegen die negativen Konsequenzen von Naturkatastrophen absichern

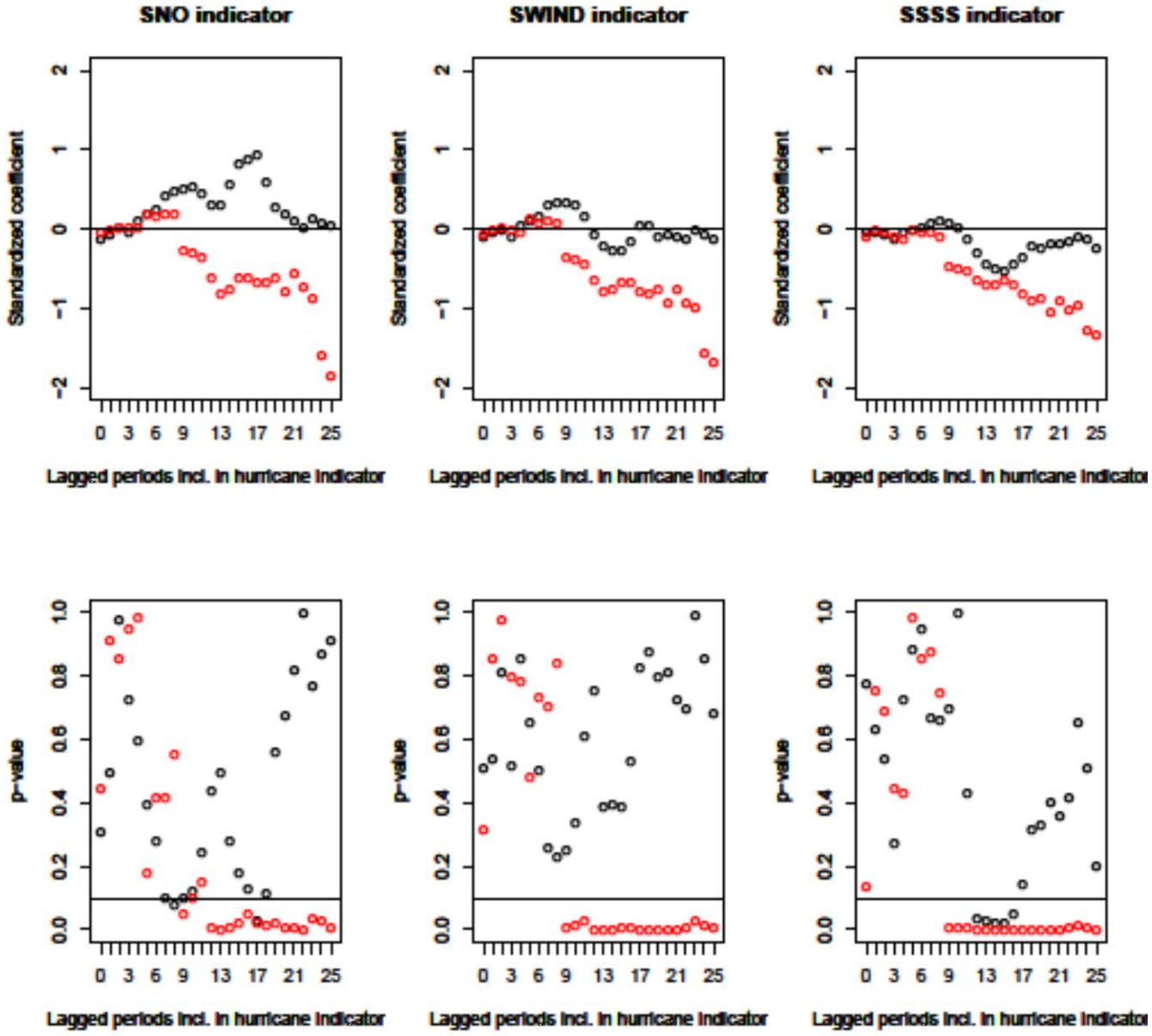
können. Zudem liefert die Untersuchung auch empirische Evidenz zu den Kanälen, durch die Naturkatastrophen das langfristige Wachstum beeinflussen. Die Ergebnisse deuten darauf hin, dass Dürren die Sparquote senken und auch die Humankapitalbildung einschränken. Gleichzeitig nimmt die Fertilität zu. Alle drei Effekte wirken im Hinblick auf das langfristige Wachstum negativ.

Abbildung 2: Schätzergebnisse Wachstumseffekte von Dürren für alternative Schätzansätze und Zeithorizonte



In einem zweiten Forschungsansatz wurden die langfristigen Wachstumseffekte von tropischen Stürmen analysiert. Die Untersuchung bezieht sich im Wesentlichen auf das gleiche Ländersample, welches bereits für die Analyse von Dürren verwendet wurde. Auch für tropische Stürme lassen sich signifikant negative, langfristige Wachstumseffekte nachweisen (vgl. Abbildung 3). In einer getrennten Schätzung für arme und reiche Länder stellt sich allerdings heraus, dass die negativen Effekte von tropischen Stürmen nur in vergleichsweise armen Ländern signifikant von null verschieden sind. Reiche Länder können sich offenbar genügend gegen die Effekte von Hurrikanen absichern.

Abbildung 3: Schätzergebnisse Wachstumseffekte von tropischen Stürmen für alternative Sturmindikatoren, Ländergruppen und Zeithorizonte



Anm.: rote Punkte indizieren vergleichsweise arme Länder, schwarze Punkte vergleichsweise reiche Länder (nach Definition der Weltbank)

Das dritte Teilprojekt befasst sich im Kern mit den möglichen Transmissionskanälen von Naturkatastrophen auf das Wirtschaftswachstum. Im Unterschied zu Teilprojekt II richtet sich der Fokus hier auf individuelle Verhaltensänderungen anstatt auf Veränderungen in aggregierten Kenngrößen. Dieser Schritt ist notwendig, da die den Veränderungen zugrundeliegenden Beweggründe nicht adäquat durch aggregierte Daten analysiert werden können. So gibt es z.B. verschiedene Gründe, warum es durch das Erleben einer Naturkatastrophe zu Änderungen im Sparverhalten kommen kann.

Der erste Forschungsansatz des dritten Teilprojekts analysiert erneut empirisch, auf Basis von Sekundärdaten, ob und wie sich das Sparverhalten von Haushalten durch das Erfahren einer Naturkatastrophe verändert. Dabei liegt der Fokus der Untersuchung auf der Jahrhundertflut in Sachsen im August 2002. Konkret werden betroffene und nicht betroffene Personen in zwei Gruppen eingeteilt und ihr Verhalten vor und nach der Katastrophe verglichen. Die Analyse basiert auf Daten des Sozio-Ökonomischen Panels (SOEP) und Überflutungsdaten für das Jahr 2002. Das SOEP ist eine in Deutschland stattfindende und sich jährlich wiederholende Umfrage, die sich an die gleichen Personen richtet. Die Daten des SOEPs erlauben demnach die Beobachtung einzelner Personen und/oder Haushalte über die Zeit. Das SOEP enthält auch Daten über das Sparverhalten von Haushalten, nicht jedoch darüber, ob ein Befragter von einer Naturkatastrophe (hier der Jahrhundertflut 2002) betroffen war. Um einzelne Individuen oder Haushalte als Betroffene zu identifizieren, bedurfte es folglich weiterer Daten, die mit den Daten des SOEPs kombiniert werden konnten. Hierzu wurden Überflutungskarten genutzt (vgl. Abbildung 4), die für den Freistaat Sachsen zur Verfügung stehen und über Geocodes der Heimatadresse der im SOEP befragten Haushalte verschnitten werden konnten. Durch Verwendung adäquater statistischer Verfahren konnte gezeigt werden, dass betroffene Individuen ihr Sparvolumen in den Folgejahren signifikant gegenüber der Gruppe von nicht betroffenen Individuen reduzierten. Ein statistisch signifikanter Effekt lässt sich in den Jahren 2004 und 2005 beobachten. Die Ergebnisse der statistischen Analyse finden sich in Tabelle 1. Es lassen sich mehrere Gründe identifizieren, die dafür verantwortlich sein könnten, dass es zu der Reduktion im Sparverhalten kommt. Letztlich erscheint es am wahrscheinlichsten, dass die Verhaltensänderung auf die generösen Hilfszahlungen seitens des Staates zurückzuführen ist, die nach der Flut an betroffene Individuen ausgezahlt wurden. Das sogenannte Samariterdilemma, bekannt aus der Entwicklungsökonomie, beschreibt, dass Individuen ihre eigene Vorsorge reduzieren, wenn ein Dritter die Kosten im Ernstfall übernimmt. Bei einer Kompensationsquote i.H.v. mindestens 80% der erlittenen Schäden ist es wahrscheinlich, dass betroffene Individuen ihr Vorsichtssparmotiv nach den Hilfszahlungen entsprechend angepasst haben.

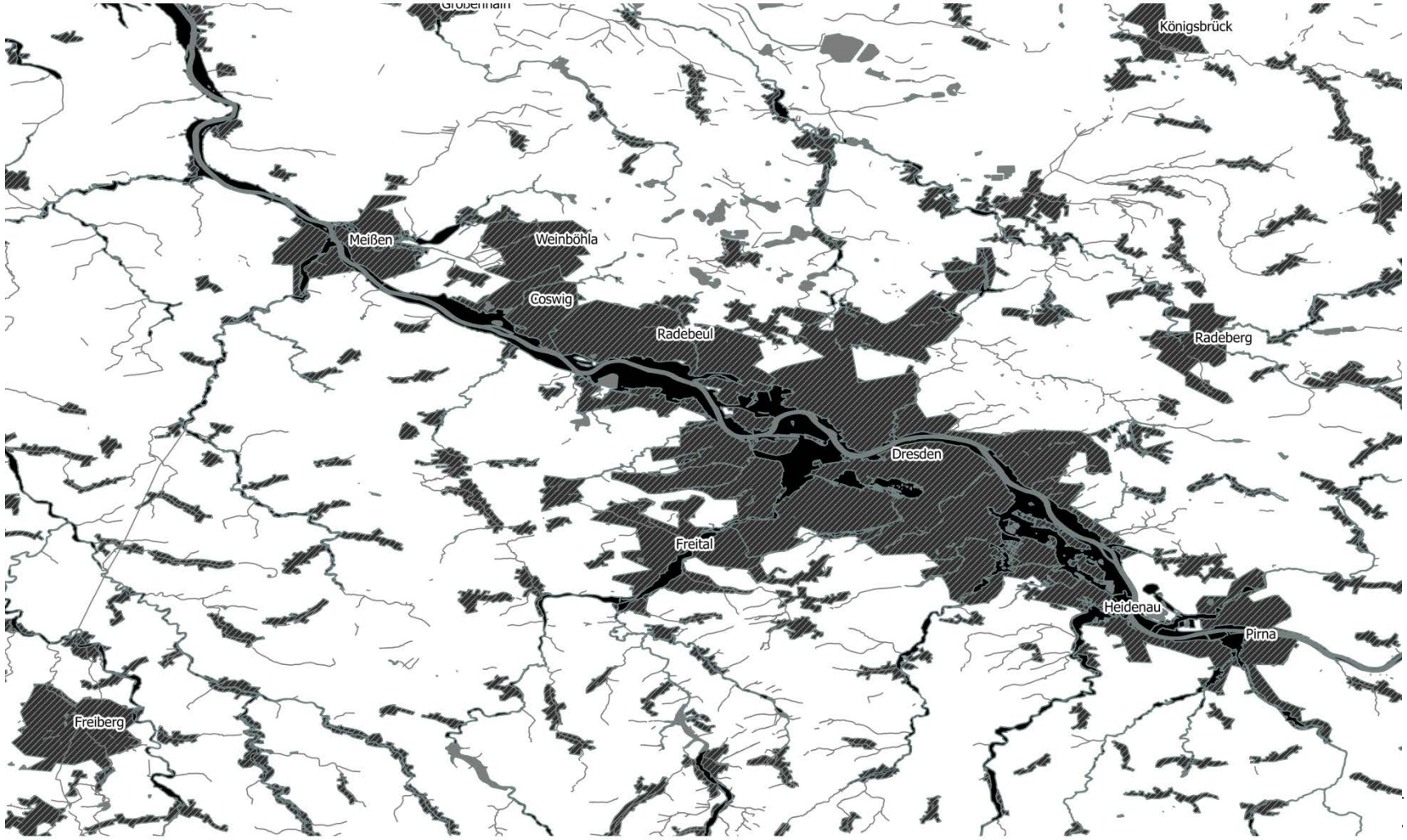

Königsbrück
Meißen
Weinböhla
Coswig
Radebeul
Radeberg
Dresden
Freital
Heidenau
Pirna
Freiberg

Tabelle 1: Reaktion des individuellen Sparverhaltens auf Flutkatastrophe

Model	Variable	2002/03	2002/04	2000/05
Tobit	Dept. Var.: *S*	(I)	(II)	(III)
	year	-8.108	-11.637	0.404
		(0.433)	(0.288)	(0.979)
	treat	-23.774	-16.321	-7.607
		(0.658)	(0.759)	(0.904)
	year x treat	-71.623	-175.168**	-178.232***
		(0.232)	(0.015)	(0.005)
	ME [E(S|S>0)]	-26.917	-59.011**	-69.631***
		(0.253)	(0.021)	(0.006)
	Change[1] (in percent)	-10.58	-25.41	-21.40
	Log pseudolikelihood	-10599.234	-9888.180	-9818.446
	Observations	2188	2068	1974
	Left censored Obs.	764	722	683
Probit	Dept. Var.: S_E			
	year	-0.068	-0.072	-0.034
		(0.224)	(0.210)	(0.604)
	treated	-0.012	0.018	0.032
		(0.965)	(0.950)	(0.913)
	year x treated	-0.163	-0.789**	-0.628**
		(0.593)	(0.026)	(0.021)
	ME	-0.058	-0.305**	-0.239**
		(0.581)	(0.018)	(0.016)
	Change[2] (in ppt.)	-5.845	-30.535	-23.91
	Log pseudolikelihood	-1285.720	-1218.389	-1155.581
	Observations	2188	2068	1974
OLS	Dept. Var.: S_I			
	year	-13.543	5.776	4.700
		(0.494)	(0.788)	(0.877)
	treated	-110.168	-75.464	-95.487
		(0.174)	(0.523)	(0.368)
	year x treated	-108.249	-133.760	-87.587
		(0.133)	(0.333)	(0.300)
	Adjusted R^2	0.122	0.128	0.123
	Observations	1276	1196	1096

Note, ME stands for marginal effect. ME are computed for a person with characteristics according to the median of all treated individuals in the respective regression sample. Observations can vary between regressions as regression samples are only balanced for the specific year-to-year combination analyzed. All regressions include the control variables depicted in table 1. The interaction terms capture the change in the differences on the outcome between before and after the flood (i.e. the effect of the flood).[1] Refers to the percentage change in saving volume due to the flood to average saving volume of a treated individual in 2002.[2] Refers to the change in the likelihood to save any amount of money due to the flood. The variable S is censored at 0. P-values are reported in parenthesis and standard errors are clustered on the household level. Significance levels:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Wie bei der Beschreibung des vorhergegangenen Forschungsansatzes gezeigt wurde, können in einzelnen Fällen, hier unter Ausnutzung eines natürlichen Experiments, kausale Schlussfolgerungen über Naturkatastrophen-bedingte Verhaltensänderungen getroffen werden. Allerdings ist diese Analyse daran gebunden, dass geeignete Daten vorliegen. Dies ist in der Realität oftmals nicht der Fall. Eine Alternative zur Analyse von Sekundärdaten stellen hier Laborexperimente dar. Solche Laborexperimente wurden in einem zweiten Forschungsansatz im Rahmen des dritten Teilprojekts durchgeführt. Wegen der oben beschriebenen Verzögerungen in diesem Teilprojekt ist die Auswertung der Experimentaldaten noch nicht vollständig abgeschlossen, so dass es zu diesem Forschungsansatz derzeit auch noch kein eigenes Forschungspapier gibt. Das Forschungsdesign und die wesentlichen Ergebnisse werden im Folgenden kurz skizziert.

Die experimentelle Untersuchung beruht direkt auf der Modellanalyse aus Teilprojekt 1. Aufbauend auf das bereits erwähnte Wachstumsmodell von Lucas und Uzawa wurde zunächst ein einfaches zweiperiodiges Experimentaldesign entwickelt. Die Grundidee ist dabei, dass (unternehmerisch tätige) Individuen typischerweise zwei Typen von Entscheidungen zu treffen haben: (1) Entscheidungen darüber, wie die zur Verfügung stehende Zeit auf Arbeitszeit und Weiterbildung aufgeteilt werden soll und (2) Entscheidungen darüber, welcher Teil des erzielten Einkommens zum Konsum und welcher zur Investition in Kapitalgüter verwendet werden soll. Im Experiment mussten die Teilnehmer tatsächlich diese Entscheidungen treffen. Im Basisspiel gab es keinerlei Unsicherheit. Daneben wurden aber auch Varianten gespielt, in denen mit im Voraus bekannten Wahrscheinlichkeiten nach der ersten Spielperiode Naturkatastrophen auftraten. Diese konnten entweder das Leben der Spieler bedrohen (natürlich nur im Experiment, was durch Spielabbruch simuliert wurde) oder das aufgebaute Kapital teilweise vernichten. Für beide Typen von Naturkatastrophen wurden Experimente mit drei verschiedenen Wahrscheinlichkeiten durchgeführt. Zusätzlich wurde auch jeweils noch eine Variante mit „Framing“ gespielt, bei der das Experimente ganz konkret im Kontext von Naturkatastrophen gespielt wurde, wohingegen ansonsten ein weitgehend neutrales Wording verwendet wurde.

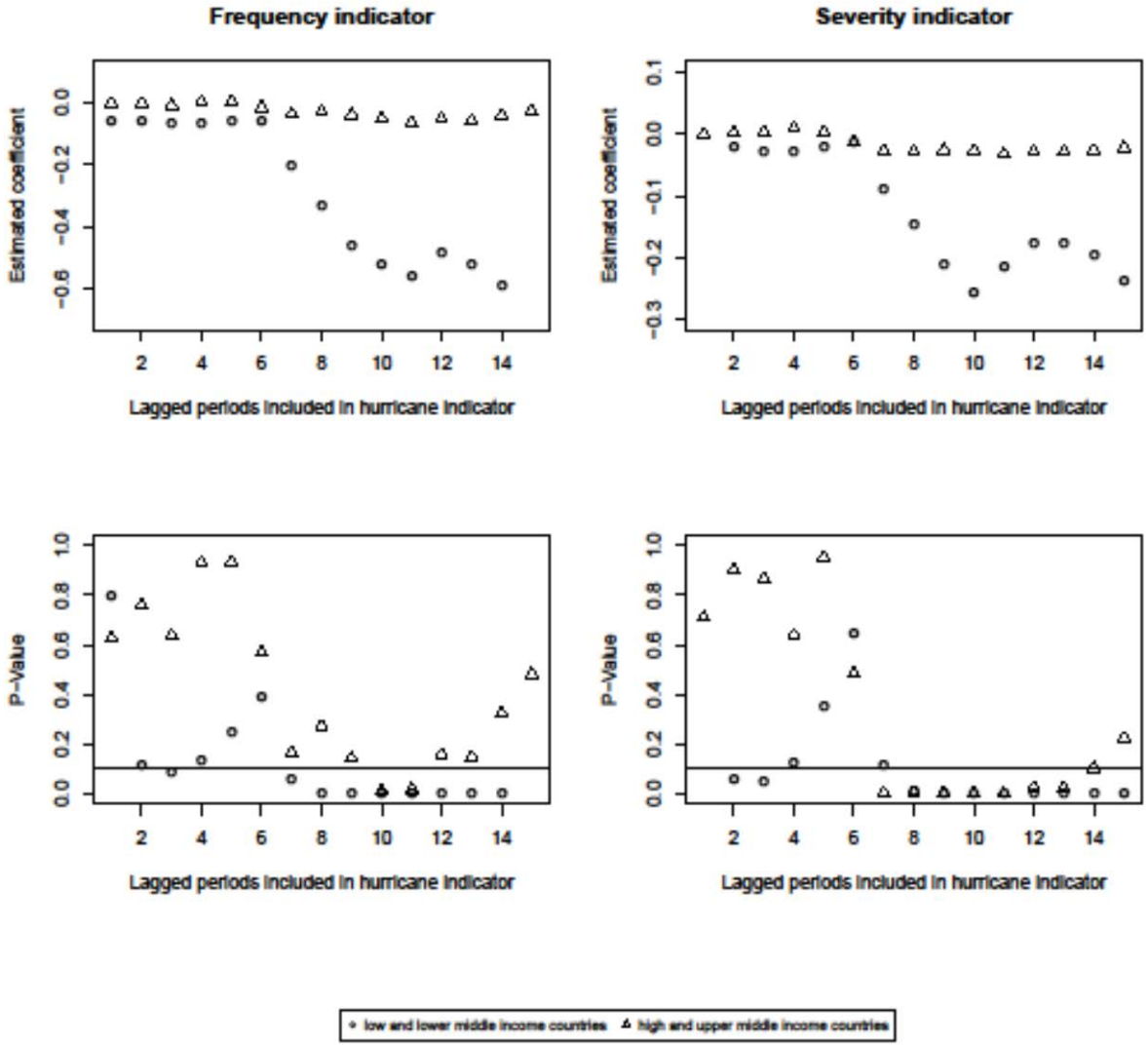
Das Experiment wurde im Frühjahr 2015 in Zusammenarbeit mit dem Meinungsforschungsinstitut „IPSOS“ durchgeführt. Insgesamt nahmen am Experiment 850 Personen teil. Jeweils 50 Personen spielten jede Variante des Experiments. Die ersten Auswertungen des Experiments haben zunächst gezeigt, dass ein erheblicher Teil der Experimentalteilnehmer mit der vergleichsweise einfachen Entscheidungssituation im Experiment bereits verständnismäßig überfordert waren. Unabhängig davon, ob diese Personen aus der Analyse ausgeschossen werden oder in der Analysegruppe verbleiben ließ sich feststellen, dass die Experimentalteilnehmer auf verhältnismäßig geringe Risiken

kaum mit einer Anpassung ihres Verhaltens reagieren. Erst wenn die Risiken verhältnismäßig stark anwachsen erfolgte auch eine deutliche Anpassungsreaktion im Hinblick auf die Akkumulation von Human- und Realkapital. Zudem deuten erste Ergebnisse darauf hin, dass auch Framing durchaus eine gewisse Rolle spielt, also Individuen im Kontext von Naturkatastrophen stärker reagieren als bei „normalen“ Lebensrisiken.

Während sich die Analysen in den ersten drei Teilprojekten im Kern auf das reale (Pro-Kopf-) Einkommen als zentralen Wohlfahrtindikator konzentrierten, wurde die Analyse im vierten Teilprojekt auf einen allgemeineren Wohlfahrtsindikator erweitert. Obwohl die Verwendung des Bruttoinlandsproduktes gängige Praxis ist, ist sie für die Untersuchung der Auswirkungen von Naturkatastrophen in mancherlei Hinsicht ein zu enges Maß. Insbesondere wird der Effekt der zunehmenden Unsicherheit der Lebensbedingungen durch eine erhöhte Auftretenswahrscheinlichkeit von Naturkatastrophen komplett vernachlässigt. Das vermehrte Auftreten von Naturkatastrophen könnte aber durchaus dazu führen, dass sich Individuen bedrohter fühlen und sich somit ihr subjektiv empfundenes Glück und/oder ihre Lebenszufriedenheit verringert. Dieser Aspekt wurde im Rahmen des vierten Teilprojekts empirisch auf der Basis von Individualdaten aus dem „Integrated European and World Value Survey“ untersucht. Konkret wurden die letzten drei Wellen dieser Befragung verwendet, die derzeit in beinahe 70 Ländern der Erde durchgeführt wird. Im Rahmen der Befragung werden die Befragten auch nach ihrem subjektiv empfundenen Glück und nach Ihrer Lebenszufriedenheit gefragt. Während die Erfragung des Glücks eher auf die momentanen Lebensumstände abzielt, beinhaltet die Lebenszufriedenheit eine längerfristige Bewertung des bisherigen Lebens und der Zukunftsperspektiven der Befragten. Um den Einfluss des Katastrophenrisikos auf die beiden Dimensionen des subjektiv empfundenen Wohlbefindens zu untersuchen, wurden die Befragungsdaten aus dem Integrated European and World Value Survey um die länderspezifischen Wahrscheinlichkeiten des Auftretens tropischer Stürme erweitert. Im Rahmen einer Panel-Ordered-Logit-Schätzung wurde dann analysiert, ob das objektive Sturmrisiko, gemessen anhand der in der jüngeren Vergangenheit aufgetretenen Stürme, einen systematischen Einfluss auf das Antwortverhalten der Befragten hatte. Die Untersuchung kommt zu dem Ergebnis, dass das subjektiv empfundene Glück lediglich dann negativ beeinflusst wird, wenn aktuell ein Sturm stattgefunden hat. Das Sturmrisiko, approximiert über längere Zeiträume, ist hingegen ohne Einfluss auf das subjektiv empfundene Glück. Anders stellt sich der Sachverhalt bei der subjektiv empfundenen Lebenszufriedenheit dar. Hier ergibt sich ein signifikant negativer Effekt auf die Lebenszufriedenheit, sobald das Sturmrisiko (sinnvollerweise) – modelliert durch das kumulierte Auftreten Stürmen – über mindestens 6 vergangene Perioden approximiert wird (vgl. Abbildung 5). Vor dem Hintergrund, dass die Lebenszufriedenheit das kognitive, längerfristig angelegte Konzept der

Messung des subjektiven Wohlbefindens ist, erscheint dieses Ergebnis als sehr plausibel. Weiterhin zeigt sich, dass die Lebenszufriedenheit sowohl in hoch wie auch in gering entwickelten Ländern negativ auf das Sturmrisiko reagiert. Allerdings ist der Effekt in ärmeren Ländern sehr viel stärker. Auch dies erscheint sehr plausibel, da die Individuen in den ärmeren Ländern auftretenden Stürmen weitgehend ungeschützt ausgesetzt sind.

Abbildung 5: Schätzergebnisse Lebenszufriedenheit und Risiko des Auftretens tropischer Stürme nach Ländergruppen und Zeithorizonten



2.2. Projektnutzen

Wie schon im Projektantrag dargelegt wurde, gab es zu Beginn des Projekts nur relativ wenig Wissen darüber, wie sich Klimawandel über die Beeinflussung der Häufigkeit und der Schwere klimabedingter Naturkatastrophen auf den langfristigen Wohlstand von Volkswirtschaften auswirkt. Die zu Projektbeginn vorliegenden Studien fokussierten vorrangig auf die Zeit direkt nach Naturkatastrophen und hatten insofern auch vorrangig Implikationen für die Soforthilfe der betroffenen Staaten. Aufbauend auf die Ergebnisse der neoklassischen und auch der endogenen Wachstumstheorie ging die Literatur zumindest implizit davon aus, dass Naturkatastrophen keine langfristigen Wachstumseffekte haben, sondern die betroffenen Volkswirtschaften nach einer gewissen Adaptionszeit von wenigen Jahren wieder auf ihren ursprünglichen Wachstumspfad zurück kehren, oder sogar durch Hilfe von außen einen Technologiesprung machen und dadurch sich langfristig sogar besser stellen als vor der Katastrophe. Die im Projekt erzielten Ergebnisse zeigen, dass diese Sicht voraussichtlich viel zu optimistisch ist. Wie im Rahmen des Projekts auf der Basis empirischer Untersuchungen gezeigt wurde, haben klimabedingte Naturkatastrophen wie Dürren und tropische Stürme durchaus negative langfristige Wachstumskonsequenzen für die betroffenen Länder. Dies gilt insbesondere für vergleichsweise arme Länder, die sich gegen die Katastrophen selbst nur unzureichend schützen können. Für diese Länder stellen Naturkatastrophen ein ernsthaftes Entwicklungshindernis dar, welches sogar geeignet ist, Länder dauerhaft in der Armutsfalle zu halten. Insofern liefern die Forschungsergebnisse eine wissenschaftliche Fundierung von Entwicklungsprojekten, die darauf abzielen, die Folgen von Naturkatastrophen abzumildern.

Zudem war bisher wenig darüber bekannt, über welche Transmissionskanäle Naturkatastrophen das langfristige Wachstum beeinflussen. Die im Projekt erzielten Forschungsergebnisse deuten darauf hin, dass mit einer Beeinflussung des Sparverhaltens, des Bildungsverhaltens aber auch der Fertilität gerechnet werden muss. Sollen die langfristigen Effekte vermieden werden, ist eine geeignete Wirtschaftspolitik notwendig. An welchen Faktoren diese ansetzen müsste, wird durch die Forschungsergebnisse aufgezeigt. Es wurde auch gezeigt, dass die von den zuständigen Regierungen nach Naturkatastrophen eingeleiteten Hilfsmaßnahmen selbst vermutlich einen Einfluss auf das zukünftige Verhalten der Betroffenen haben. So fanden sich im Rahmen des Projekts Hinweise darauf, dass großzügige Kompensationen seitens des Staates Maßnahmen zur Eigenvorsorge einschränken.

Auch wenn die Projektergebnisse darauf hindeuten, dass für hoch entwickelte Länder die langfristigen Wachstumskonsequenzen eher überschaubar sind und vor allem die ärmeren Länder hierunter leiden, lieferte das Projekt auch Ansatzpunkte dafür, dass schon die bloße Gefahr des

Auftretens von Naturkatastrophen die empfundene Lebenszufriedenheit senkt. Somit gibt es durchaus auch in bereits hoch entwickelten Ländern Gründe, Maßnahmen zum Schutz vor Naturkatastrophen zu ergreifen.

2.3. Fortschritte bei anderen Stellen

Während der Projektlaufzeit wurde eine Reihe von wissenschaftlichen Studien zum Thema Klimawandel, Naturkatastrophen und Wirtschaftswachstum publiziert. Diese Literatur wurde in den eigenen Publikationen zum Thema aufgearbeitet und zu den eigenen Arbeiten ins Verhältnis gesetzt. Der Novitätsgehalt der eigenen Arbeiten hat hierunter nicht gelitten; vielmehr entsteht hierdurch ein insgesamt zunehmend kohärentes Bild. Auf eine detaillierte Darstellung der neu entstandenen Literatur wird hier verzichtet und stattdessen auf die beigefügten Publikationen (vgl. Anhang) verwiesen.

2.4. Veröffentlichungen:

Bereits fertiggestellte Publikationen (vgl. Anhang):

- Michael Berlemann & Daniela Wenzel (2015), Long-term Growth Effects of Natural Disasters - Empirical Evidence for Droughts, CESifo Working Paper No. 5598, CESifo Munich (Status: Revised & Resubmitted to: Economics Bulletin).
- Michael Berlemann, Max Steinhardt & Jascha Tutt (2015), Do Natural Disasters Stimulate Individual Saving? Evidence from a Natural Experiment in a Highly Developed Country, IZA Discussion Paper No. 9026, IZA Bonn (Status: Under Review at: Journal of Monetary Economics).
- Michael Berlemann (2014), Hurricane Risk, Happiness and Life Satisfaction. Some Empirical Evidence on the Indirect Effects of Natural Disasters, Working Paper, Helmut-Schmidt-University Hamburg (Status: Revise & Resubmit to: Ecological Economics).
- Michael Berlemann & Daniela Wenzel (2015), Long-term Growth Effects of Tropical Storms. Empirical Evidence for Developed and Underdeveloped Countries, Working Paper, Helmut-Schmidt-University Hamburg (Status: Under Review at: Journal of Development Economics).

3. Erfolgskontrollbericht

Im nicht öffentlichen Teil des Anhangs

4. Kurzfassung

4.1. Berichtsblatt

1. ISBN oder ISSN: nicht geplant	**2. Berichtsart:** Schlussbericht
3. Titel Globale Erwärmung, Naturkatastrophen und ökonomische Konsequenzen	
4. Autoren: Berlemann, Michael Michailova, Julija Tutt, Jascha Wenzel, Daniela	**5. Abschlussdatum des Vorhabens:** Juni 2015 **6. Veröffentlichungsdatum:** 30.11.2015 **7. Form der Publikation:** Bericht
8. Durchführende Institution: Helmut Schmidt Universität Universität der Bundeswehr Hamburg Holstenhofweg 85 22043 Hamburg	**9. Ber. Nr. Durchführende Institution:** UT 221 **10. Förderkennzeichen:** 01LA1116A **11. Seitenzahl:** 26
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16. Zusätzliche Angaben: /	
17. Vorgelegt bei: /	
18. Kurzfassung Im Zuge des Klimawandels treten bestimmte Typen von Naturkatastrophen häufiger und/oder stärker auf. Vor diesem Hintergrund stellt sich die Frage, ob und über welche Kanäle Naturkatastrophen die langfristige Entwicklung von Ländern beeinflusst. Auf Basis empirischer und experimenteller Methoden konnte gezeigt werden, dass Dürren und tropische Stürme tatsächlich langfristig negative Wachstumseffekte aufweisen, insbesondere in vergleichsweise armen Ländern, die sich weniger gut gegen die Folgen von Naturkatastrophen absichern können. Naturkatastrophen können unterschiedlichste Verhaltensveränderungen bewirken, so z.B. Veränderungen des Sparverhaltens, der Humankapitalbildung und der Fertilität. Es gibt aber auch Hinweise darauf, dass die nach Naturkatastrophen ergriffenen staatlichen Maßnahmen einen Einfluss auf das spätere Verhalten von Betroffenen haben. Schließlich zeigt sich, dass schon das bloße (nicht realisierte) Naturkatastrophenrisiko einen wohlfahrtsmindernden Effekt hat. Erhöhte Unsicherheit erzeugt also tatsächlich ökonomisch bewertbare soziale Kosten.	
19. Schlagwörter: Naturkatastrophen, Klimawandel, Wirtschaftswachstum, Lebenszufriedenheit, Empfundenes Glück, Sparverhalten, Fertilität, Bildung, Samariter-Dilemma, Entwicklungsländer	
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1. ISBN or ISSN: not planed	**2. type of document:** final report
3. title Global warming, natural disasters and economic consequences	
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8. performing institution (name, address) Helmut Schmidt University University of the federal armed forces Hamburg Holstenhofweg 85 22043 Hamburg	**9. originator's report no.:** UT 221 **10. reference no.:** 01LA1116A **11. no. of pages** 26
12. sponsoring agency: Bundesministerium für Bildung und Forschung (BMBF) 53170 Bonn	**13. no. of references** 18 **14. no. of tables** 1 **15. no. of figures** 5
16. supplementary notes: /	
17. presented at: /	
18. abstract As a consequence of climate change, certain types of natural disasters occur more often and/or more severe. Against this backdrop the question occurs whether natural disaster go along with long term growth effects. Based on empirical and experimental methods we showed that droughts and tropical storms cause negative long term growth effects, which are especially pronounced in comparatively poor countries which cannot protect against disasters easily. Natural disasters can cause a multitude of behavioral changes which promote the negative growth effects concerning issues such as saving behavior, human capital formation and fertility. However, we also present empirical evidence in favor of the hypothesis that governmental post-disaster help has an influence on precautionary measures undertaken by the affected individuals. Finally, we find that the increasing risk of natural disasters itself decreases self-reported life satisfaction even when it does not materialize in concrete disasters.	
19. keywords: Natural Disasters, Climate Change, Economic Growth, Life Satisfaction, Happiness, Saving Behavior, Fertility, Human Capital, Samaritan's Dilemma, Developing Countries	
20. publisher: not planed	**21. price:** not planed

Anhang

Forschungspapiere

Im Folgenden finden sich die einzelnen Forschungspapiere

1. “Long-term Growth Effects of Natural Disasters: Empirical Evidence for Droughts”
2. “Long-term Growth Effects of Tropical Storms: Empirical Evidence for Developed and Underdeveloped Countries”
3. “Do Natural Disasters Affect Individual Saving? Evidence From a Natural Experiment in a Highly Developed Country”
4. “Hurricane Risk, Happiness and Life Satisfaction”

Long-term Growth Effects of Natural Disasters
Empirical Evidence for Droughts

Michael Berlemann*

Daniela Wenzel#

Abstract

The ongoing process of climate change goes along with a higher frequency and/or severity of droughts. While the short-term growth consequences of droughts are comparatively well examined, little research has yet been devoted to the question whether and how droughts affect medium and long-term growth. However, knowledge on the growth dynamics triggered by natural disasters is an influential input factor for integrated assessment models which are used to evaluate climate policy measures. In this paper we deliver empirical support for the hypothesis of the existence of long-run growth effects of droughts. Based on a panel of 153 countries over the period of 1960 to 2002 and employing a truly exogenous drought indicator derived from rainfall data we find significantly negative long-term growth effects of droughts in both highly and less developed countries. We also deliver first empirical evidence on the channels through which droughts affect economic growth.

JEL code: Q54, O16, H84

Keywords: Climate change, natural disasters, droughts, economic growth, transmission channels

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1. Introduction

A likely consequence of the ongoing process of climate change is an increased frequency and/or severity of certain types of natural disasters and extreme weather events (Thomas 2014). Against this backdrop, there has been an increasing interest in the question of whether and how natural disasters affect economic growth. Most of the existing empirical evidence concerns the short-term effects of natural disasters and tends to find negative short-term growth effects of natural disasters (see, e.g., Felbermayr and Gröschl 2014). Much less empirical evidence is available on the long-term growth effects of natural disasters. Moreover, the few existing empirical studies deliver mixed results. In their cross-sectional study of 89 countries, the pioneering paper by Skidmore and Toya (2002) finds different results for climatic and geologic disasters. Whereas the frequency of climatic natural disasters turns out to have a positive effect on economic growth, geologic disasters tend to have a negative although insignificant impact on economic growth. Noy and Nualsri (2007) find negative growth impacts of natural disasters with high casualty numbers but no significant effects of disasters damaging the capital stock. Similar results are reported in Jaramillo (2009). However, Raddatz (2009) finds climatic disasters to have a negative long-run impact on economic growth. In their review of the related literature, Cavallo and Noy (2010) conclude "A further significant lacuna in the current state of our knowledge is the absence of any agreement regarding the long-run effects of these disasters".

One might suspect that three reasons are responsible for the relatively mixed picture. First, it seems to be questionable to treat all (climatic) disasters as homogenous, as one might easily imagine different disasters to affect economic development differently. Second and even more problematic, inappropriate measurement of natural disaster severity might have contributed to the yet ambiguous results (see also Cavallo and Noy 2010). The vast majority of existing studies relies on data from the EM-DAT database. As Strobl (2012) argues, the EM-DAT data was collected from various different sources and thus is likely contaminated with measurement error since the reporting sources differ in their motives, methodologies and quality of reporting disaster damages. Moreover, using the EM-DAT disasters intensity indicators likely leads to an endogeneity problem in growth regressions as (i) the monetized damage of a disaster and (ii) insurance coverage and thus the probability of inclusion into the database depend on per capita GDP, the dependent variable in growth regressions (Felbermayr and Gröschl 2014). Third, by far the most empirical studies of the growth effects of natural disasters regress GDP growth on a number of control variables (such as the saving rate, fertility or human capital) and add a measure of disaster frequency or severity to the estimation equation. As the effect of natural disasters on economic growth might work through exactly these control variables, an “over-controlling problem” is likely to occur which might result in insignificant effects of the disaster indicator (Dell, Jones and Olken 2014).

In a recent paper Hsiang and Jina (2014) show how these problems can be tackled adequately. In their study the authors concentrate on one type of natural disasters, tropical cyclones. Instead of using EM-DAT data the authors rely on truly exogenous meteorological measures of cyclone severity. And finally, the authors refrain from using control variables in their main analysis and get rid of cross-country and time variance by applying time and country-fixed effects, a solution which has also been proposed by Dell, Jones and Olken (2014).

In this paper we study the effect of droughts on long-term economic growth. We thereby follow the approach of Hsiang and Jina (2014) and identify droughts on the basis of a rainfall-indicator. In our baseline panel regression approach we refrain from using possibly multicollinear control variables. We find robust empirical evidence in favor of the hypothesis that droughts depress long-term economic growth in both highly developed and less developed countries. We also shed light on the channels through which droughts affect economic growth.

The remainder of the paper is organized as follows. In the second section, we outline the estimation approach and present the employed data. Section three delivers the estimation results. Section four analyzes growth effects in different country groups and section five is concerned with possible transmission channels. Section six summarizes.

2. Estimation Approach and Data

Our estimation approach consists of estimating panel regressions of the type:

$$\ln GDP_{t,i} - \ln GDP_{t-1,i} = \alpha_i + \beta_t + \gamma \cdot D_{i,t,k} + \varepsilon_{i,t} \quad (1)$$

where ln GDP is the natural logarithm of the per capita gross domestic product in country i at time t, α_i is a country fixed effect controlling for countries' differing institutions, cultures and geographies, β_t are time fixed effects, $D_{i,t,k}$ is an indicator of drought severity in the actual and the k preceding years and $\varepsilon_{i,t}$ is the unexplained residual. In order to control for autocorrelation for up to 10 years and heteroscedasticity we estimate the model using ordinary least squares and HAC standard errors (Newey and West 1987). We also control for possible spatial correlation within a distance of 1,000 km (Conley 1999, Hsiang 2010 and Fetzer 2014).

The variable of central interest, the meteorological drought indicator $D_{i,t,k}$ is constructed from data provided by the International Research Institute for Climate and Society (IRI). Different from the often employed disaster indicators from the EM-DAT database our indicator is by construction exogenous as it is calculated solely on the basis of precipitation data, which itself is unaffected by economic growth. We make use of the Standardized Precipitation Index (SPI) which was initially developed by McKee, Doesken and Kleist (1993) and was recommended by the leading researchers in the field in the Lincoln Declaration on Drought Indices (World Meteorological Organization 2012). Our drought indicator at time t is defined as the average of the absolute value of the sum of all negative 12-month-SPI-values over the actual and the k preceding years in country i (per mio. sqkm):

$$D_{i,t,k} = \frac{\sum_{j=0}^{k} \sum_{m=1}^{12} \left| SPI_{i,t-k,m}^{neg.} \right|}{k+1}$$

The utilization of this sort of indicator allows us identifying whether droughts affect economic growth only in the very short-run (in this case only the versions of the indicator including the directly preceding years should turn out to be significant) or whether the medium and long-run disaster history is (also) relevant.

We use Penn World Tables Version 8.0 as source of GDP data (Feenstra, Inklaar and Timmer 2015) and construct our left hand variable from GDP per capita in constant prices of 2005 (RGDPNA). For the initial level of GDP per capita we use current GDP (output side, current PPP). For stability tests we also use the standard set of control variables, e.g. the investment share of real GDP per capita (PWT 8.0), the government share of real GDP per capita (PWT 8.0), the net fertility rate (World Development Indicators, calculated) and the average years of total schooling (Barro and Lee 2013, linearly interpolated). Table 1 delivers summary statistics of the employed dataset.

Table 1: Summary statistics of employed dataset

Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min*	*Max*
Real GDP per capita (RGDPNA), prices of 2005	4665	0,04	0,07	-1,08	0,72
Log of current GDP, output side (current PPP)	4788	9,59	1,91	3,96	15,44
Sum of neg. SPI-values (abs. value per mio. sqkm)	6063	2857,42	3221,95	0,00	72237,38
Investment share in real GDP per capita (RGDPL), %	4787	0,18	0,11	0,01	1,40
Gov. share in real GDP per capita (RGDPL), %	4788	0,21	0,13	0,01	1,44
Net fertility rate	4453	4,16	1,48	1,06	7,79
Avg. years of total schooling, linearly interpolated	5194	4,43	2,82	0,02	12,71

Sources: International Research Institute for Climate and Society, Penn World Tables 8.0, World Development Indicators, Barro and Lee 2013.

Altogether, our unbalanced panel dataset consists of data from 153 countries and covers the years of 1960 to 2002.[1] The number of years included differs in between 12 and 43.

3. Estimation Results

Figure 1 summarizes the results of our baseline panel estimation and two additional specifications of model (1). [2] In the upper part we show the coefficients of the baseline model with two-way fixed effects and without any control variables.[3] All coefficients turn out to be negative, and, with the exception of the one-period lagged version, are significant on at least the 90%-confidence-level. Moreover, the effects are comparatively large as an increase of one standard deviation in the drought indicator leads to negative growth effects in between 1.5 and 8.5 percentage points (depending on the specification). Thus, we find strong supporting evidence for the hypothesis that droughts have significant long-lasting effects on economic growth.

[1] The dataset covers countries of all levels of development, although (as usual) especially some highly underdeveloped countries had to be excluded due to missing data.

[2] We made use of the Im-Pesaran-Shin Test to ensure that the employed data is stationary. The test results are available from the authors on request.

[3] Due to space restrictions we refrain from reporting the complete estimation results here; however, they are available from the authors on request. The explanatory power of the estimations as measured by adjusted R squared ranges in between 0,10 and 0,11.

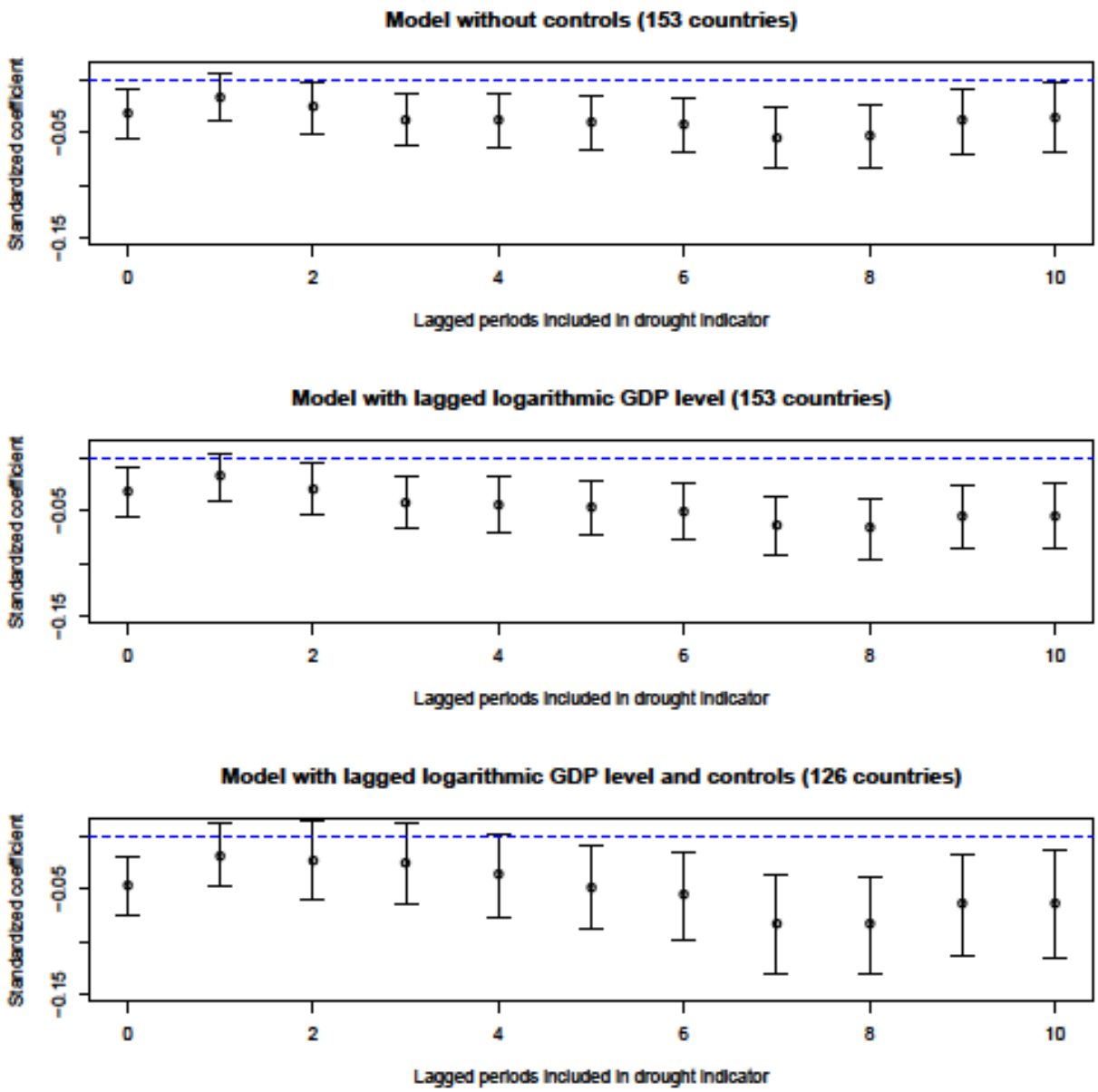

Figure 1: Estimation results for growth effects of droughts for alternative specifications (point estimator and 90%-confidence intervals)

In order to test the stability of our results we repeat the estimation for two alternative specifications. In a first alternative specification, shown in the middle of Figure 1, we additionally control for the level of development of a country by adding the logarithmic one-period ahead GDP level to the estimation equation, as it is typically done in growth regressions.[4] When doing

[4] When including the logarithmic level of GDP as control the resulting model might suffer from the well-known Nickell Bias (Nickell 1981). However, as the average time dimension of our panel data is large (36 years) it seems to be

so, the estimated coefficients of the drought indicator slightly increase in absolute value. At the same time the p-values of the estimated coefficients increase. The estimated coefficients of the drought indicator further increase when employing the full set of control variables typically used in growth regressions (net fertility, education, savings rate and government consumption share)[5] as shown in the lower part of Figure 1. However, the p-values of the drought indicator decrease in this specification, likely due to the earlier described over-controlling problem. Nevertheless, the estimated coefficients of the drought indicator remain significant at least for specifications including at least the preceding 5 years.

While we cannot document all estimations underlying Figure 1 here in length, due to space restrictions, we show the estimation results for the indicator covering the 5 years preceding the drought in Table 2. Whenever the initial GDP level is added to the regression equation it turns out to be significant and negative, as most growth theories predict. In the specification with full set of controls the savings rate (investment share) and the net fertility rate turn out to be significant. While a higher savings rate increases per-capita growth the opposite holds true for net fertility. Again, both findings are in line with conventional theories of economic growth. The other employed control variables turn out to be insignificant.

Table 2: Selected estimation results for 5-year drought indicator

	(1)	(2)	(3)
Drought indicator $_{i,t,5}$	-0.0423***	-0.0483***	-0.0500**
	(0.0158)	(0.0159)	(0.0245)
Ln GDP $_{i, t-1}$		-1.4473***	-1.4543***
		(0.2273)	(0.2692)
Investment share $_{i, t-1}$			0.1000**
			(0.0418)
Government share $_{i, t-1}$			0.0224
			(0.0487)
Net fertility rate $_{i, t-1}$			-0.1054*
			(0.0597)
Avg. years of total schooling $_{i, t-1}$			-0.0883
			(0.1111)
Observations	5035	5035	4127
Countries	153	153	126
Adjusted R^2	0.1054	0.1358	0.1520

***,**,* denote significance at the 1%, 5% and 10% level, respectively. Spatially corrected HAC standard errors reported in parentheses. Country and time fixed effects are included but not reported.

appropriate to assume that the remaining bias is small enough to be neglected. The explanatory power of the estimations as measured by adjusted R squared ranges in between 0,13 and 0,14.

[5] In all specifications significant control variables have the expected sign. The explanatory power of the estimations as measured by adjusted R squared ranges in between 0,15 and 0,16.

4. Does the Effect of Droughts Differ between Rich and Poor Countries?

Earlier empirical findings (see e.g. Skidmore and Toya 2007 or Kahn 2004) have pointed into the direction that certain types of natural disasters might have different effects in rich and in comparatively poor countries, for example because comparatively rich countries can invest more resources into disaster prevention and mitigation measures. In order to study potential differences in drought-effects we subdivided our sample into two subsamples. The first subsample consists of 29 countries which are classified as high income countries by the World Bank. The remaining 122 countries form the second subsample. For both subsamples we repeat the two-way fixed effects estimation.

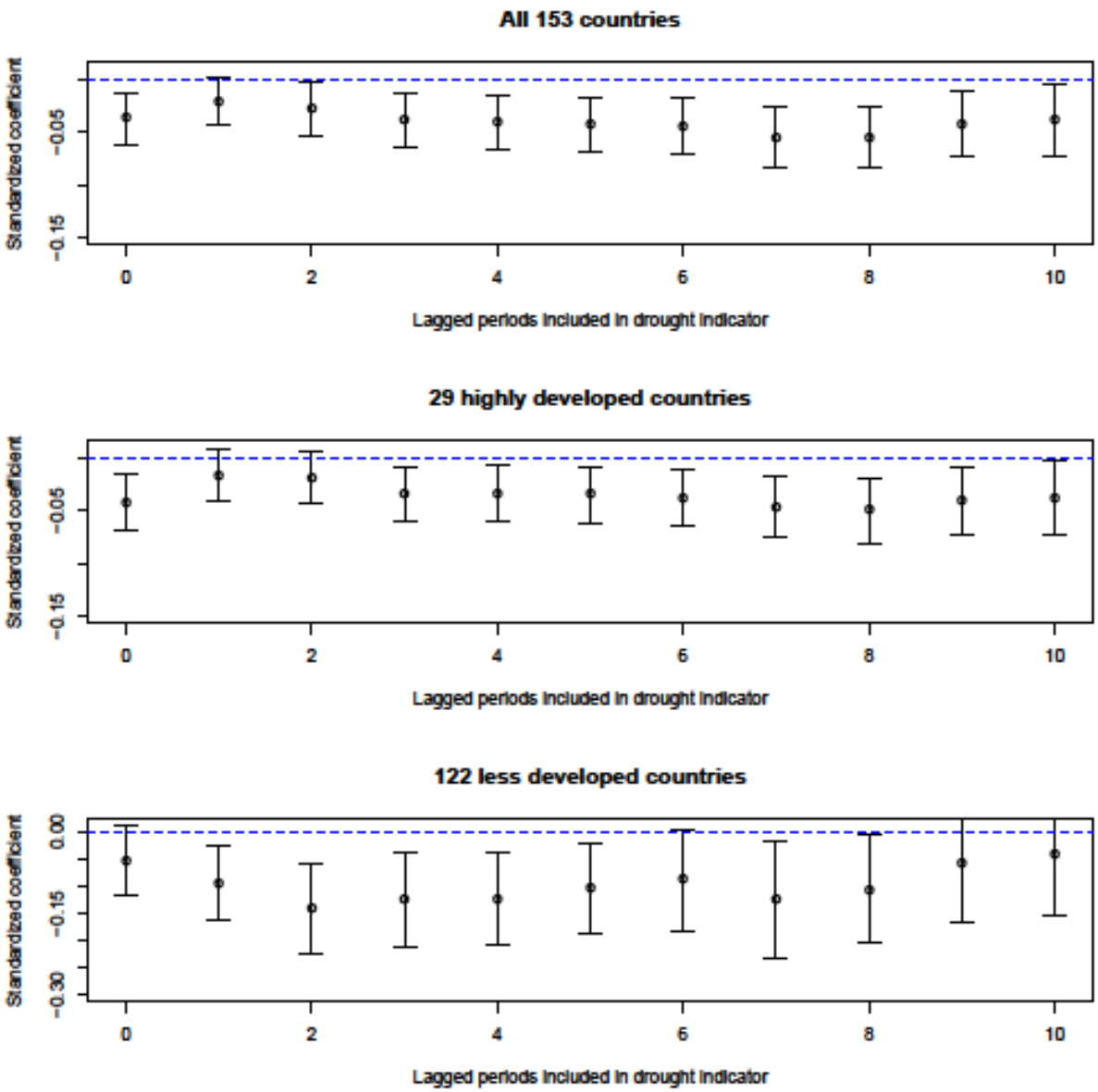

Figure 2: Estimation results for growth effects of droughts for country groups (point estimator and 90%-confidence intervals)

The estimation results for the drought indicators are shown in Figure 2. The results indicate that in both highly developed and less developed countries droughts tend to affect economic growth negatively, although the time patterns differ to some extent. Moreover and in line with the earlier cited literature, we find the effects of droughts to be much larger in the sample of less developed countries.

5. Transmission Channels

As our previous analysis has detected significantly negative long-run effects of droughts one might be interested in the question, through which channels droughts affect long-run economic growth. Because long-run growth effects themselves have only rarely been studied it does not come as a surprise that only scarce evidence is yet available on the issue of transmission channels of natural disasters in general and droughts in particular. The natural candidates for transmission channels can be identified on the basis of theories of economic growth. Although the factors determining long-run growth naturally differ to some extent in between competing theories, factors such as the savings rate, the rate of population growth and human capital play a decisive role in almost all modern growth theories. We therefore concentrate our analysis on these growth factors and study whether the savings rate, net fertility and education are affected by occurring droughts.

Saving is typically seen as a means of consumption smoothing. Naturally, the amount of saving will increase with a corresponding increase in life expectation. Whenever natural disasters pose a risk to life, this likely increases consumption and depresses saving. However, the theory of precautionary saving argues that saving does not only serve to spread income over the life cycle, but might also serve as insurance against uncertain events (Lusardi 1998). In this context, Roson et al. (2005) argue that individuals might react to natural disasters by increasing their savings. However, it is also possible that precautionary saving is reduced as a consequence of natural disasters. Often individuals who have suffered from catastrophic losses are supported or even compensated by state institutions, private donations, or international aid. All these forms of support decrease the incentives for accumulating one's own precautionary savings.

Natural disaster risk might also affect population growth. Especially in less developed countries children are a means of smoothing consumption over time (Guarcello, Mealli and Rosati 2010). Whenever households experience losses of income and/or wealth, the birth of additional children can, at least in the medium- and long-run, help the parents to enhance their financial situation, e.g. by generating supplemental income or taking over roles in family life which allows both parents to be part of the labor force. Whenever disaster risk poses not only a threat to income and wealth but also to life, parents might choose to increase their number of children as an insurance against child mortality (Schultz 1997).

Finally, human capital accumulation might be affected by natural disaster risk. On the one hand, natural disasters tend to reduce the expected return to physical capital, which should increase the incentive to invest in human capital (Skidmore and Toya, 2002). On the other hand, whenever disaster risk also increases mortality, the return of educational investments decreases and makes human capital accumulation less attractive (Checchi and Garcia-Penalosa 2004). Natural disasters

might also have negative effects of human capital accumulation via decreasing educational attainment, e.g. in consequence of evacuations, increasing drop-out rates or school switching (Sacerdote 2012).

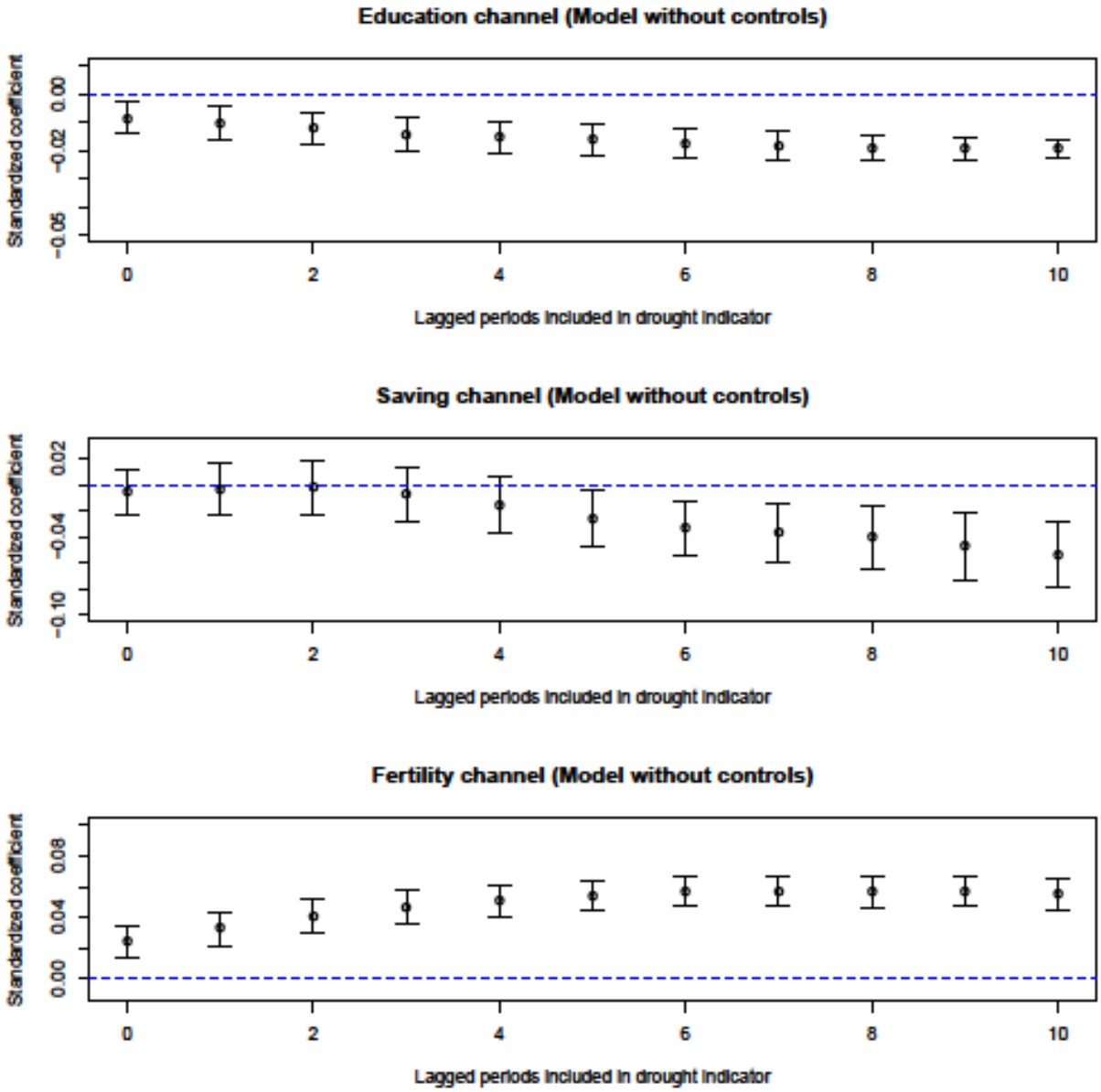

Figure 3: Estimation results for alternative transmission channels of droughts (point estimator and 90%-confidence intervals)

In order to investigate the relevance of the discussed transmission channels empirically we apply the same estimation approach employed earlier to study the long-term growth effects of droughts, i.e. two-way fixed effects panel regressions with spatially corrected HAC standard

errors. [6] In order to avoid multicollinearity problems we again refrain from using additional control variables.[7]

In the upper part of figure 3 we show the effects of a one standard deviation increase in the drought indicator on the average years of total schooling. The estimated effect is negative and significant for all versions of the indicator. Thus, droughts tend to depress human capital formation. Our results coincide with the relatively small existing empirical literature which mostly finds negative effects of natural disasters on human capital accumulation. Alderman, Hoddinott and Kinsey (2006) study the effect of droughts on human capital formation in rural Zimbabwe and find a significantly negative effect on the number of completed school grades. Alston and Kent (2006) study the drought impact in secondary education access in Australia's rural and remote areas based on interviews and find evidence that droughts decrease human capital formation on the level of primary as well as on high schools. Cuaresma (2010), based on a sample of 80 countries over the period of 1980 to 2000, finds geologic disasters to depress secondary school enrollment while no such effect exists for climatic disasters. Kim (2010) studies the effect of two droughts in Cameroon and Burkina Faso based on a combination of survey and EMDAT data. While he finds a significantly negative effect of the 1990 drought on primary school completion in Cameroon, the effect for the 1988 drought in Burkina Faso turns out to be insignificant.[8]

In the middle part of figure 3 we show the effects of a one standard deviation increase in droughts on saving. The saving rate tends to react to droughts; all estimated coefficients turn out to be negative. However, the effect is significantly different from zero only when basing the drought indicator on at least the 5 preceding periods. Thus, droughts tend to depress saving at least in the medium term perspective. To the best of our knowledge the only related study by Skidmore and Toya (2002) found a negative but insignificant effect of climatic disasters on saving.

In the lower part of figure 3 we show the effects of a one standard deviation increase in the drought indicator on net fertility. The estimated coefficient is positive and significant for all variants of the indicator. Thus, droughts tend to increase net fertility, a result which is in line with the scarce empirical evidence on different types of natural disasters on fertility. In their empirical analysis of the December 2004 Indian Ocean Tsunami Nobles, Frankenberg and Thomas (2014) find a subsequent increase in fertility in the affected region. Finlay (2009) studies the fertility reaction after three huge earthquakes in India, Pakistan and Turkey and again reports long-lasting increases of fertility rates.

[6] Again we made use of the Im-Pesaran-Shin Test to check whether the employed data is stationary. The test results are available from the authors on request.

[7] The results are similar when using the initial GDP level to control for countries' level of development. The results are available from the authors on request.

[8] Kim (2010) also shows that wild fires in Mongolia reduced the probability to complete secondary school significantly.

6. Summary and Conclusions

In this paper, we extend the existing literature on the long-term growth effects of natural disasters by studying the effects of droughts, based on a meteorological indicator constructed from rainfall data. We find systematically negative effects of droughts on the long-term growth performance of drought-affected countries which are of economically meaningful size and work through at least three different channels: lower education levels, lower saving rates and higher fertility.

The importance of this finding can be highlighted in the context of Integrated Policy Assessment Models (IAMs) which are the most widely used instrument of forecasting the economic consequences of climate change (see e.g. Metcalf and Stock 2015). As a prominent example, these models are used to estimate the necessary levels of carbon taxes to be able to reach pre-defined emission targets. IAMs combine information about human behavior and climate systems. An integral part of IAMs are damage functions. A major issue in modeling damage functions is whether climate (or climate-induced natural disasters) affects the level of output, as most IAMs assume, or impacts the growth path of output (Dell, Jones and Olken 2014). As the dynamic specification of the damage function has a huge impact on the forecast results and thus on the policy conclusion derived from IAMs a better empirical foundation of the damage function is highly important. Our results indicate that damage functions should assume climate to affect the path of output growth rather than only the level of output.

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Long-term Growth Effects of Tropical Storms

Empirical Evidence for Developed and Underdeveloped Countries

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While the short-term growth consequences of natural disasters are comparatively well studied, there is little knowledge how disasters affect long-run growth. Based on truly exogenous storm indicators, derived from a meteorological database, we show that the growth effects of tropical storms go well beyond the short-term perspective. We also show that the negative growth effects of hurricanes are especially pronounced in developing countries which have comparatively little possibilities to protect against storm consequences.

Keywords: Economic Growth; Natural Disasters; Tropical Storms

JEL classification: I31,Q54

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1 Introduction

Early research on the economic effects of natural disasters focused on the direct impact of disasters on economic activity (see, e.g., Raddatz 2007, Noy 2009, Felbermayr and Gröschl 2014). In their comprehensive analysis of the short-term effects of different sorts of natural disasters Felbermayr and Gröschl (2014) conclude that the effect of natural disasters on short-term economic growth is ”naturally negative”. Little research has been conducted on the medium- or long-term growth consequences of natural disasters. The likely reason for the research focus on short-term growth effects is that according to standard neoclassical growth theory a natural disaster has no effect on long-run per-capita GDP. Interpreting a disaster as a shock on a country's capital shock (or population), this shock leads to a negative (positive) effect on per-capita income in the short-run. However, as a consequence of a temporarily rising per-capita savings rate the capital stock will rise to its intial per-capita level, leaving the economy without a long-term growth effect.

However, the view that natural disasters leave long-term growth unaffected might be wrong. Many natural disasters occur quite often in certain regions. Within the ongoing process of climate change the frequency and/or severity of certain types of natural disasters and extreme weather events will likely further increase (Milly et al. 2002, Hoyos et al. (2006), van Aalst (2006), Solomon et al. (2009), Thomas 2014). Repeatedly occurring disasters might prevent that countries reach their long-term equilibrium and never recover from the disaster effects. Moreover, the implicit assumption of neoclassical growth theory that individual saving behavior, education decisions or fertility remain unaffected by disasters is unlikely to hold in reality (see e.g. Berlemann, Steinhardt and Tutt 2015 or Berlemann and Wenzel 2015).

Only recently, empirical research on the long-run growth effects of natural disasters intensified. However, the existing empirical evidence is yet inconclusive.[1] In their literature review, Cavallo and Noy (2010) come to the conclusion "A further significant lacuna in the current state of our knowledge is the absence of any agreement regarding the long-run effects of these disasters". One might suspect that three reasons are responsible for the relatively mixed picture. First, it seems to be questionable to treat all (climatic) disasters as homogenous, as one might easily imagine different disasters to affect economic development differently. Second and even more problematic, inappropriate measurement of natural disaster severity might have contributed to the yet ambiguous results (see also Cavallo and Noy 2011). The vast majority of existing studies relies on data from the EM-DAT database. As Strobl (2012) argues, the EM-DAT data was collected from various different sources and thus is likely contaminated with measurement error since the reporting sources differ in their motives, methodologies

[1] See e.g. Skidmore and Toya (2002), Noy and Nualsri (2007), Jaramillo (2009) and Raddatz (2009)

and quality of reporting disaster damages. Moreover, using the EM-DAT disasters intensity indicators likely leads to an endogeneity problem in growth regressions as (i) the monetized damage of a disaster and (ii) insurance coverage and thus the probability of inclusion into the database depend on per capita GDP, the dependent variable in growth regressions (Felbermayr and Gröschl 2014). Third, the effects of natural disasters on long-term growth might depend on the level of development of a country, as highly developed countries can protect themselves much better against the consequences of natural disasters than less developed countries (Skidmore and Toya 2007).

In this paper we contribute to the literature by studying the short-, medium- and long-run growth effects of tropical storms within a unified panel estimation approach. Instead of using EM-DAT data we rely on truly exogenous meteorological storm data to construct appropriate hurricane indicators. Special attention is devoted to the question whether hurricane effects differ in between highly developed and underdeveloped countries.

The remainder of the paper is organized as follows. In the second section, we review the related literature. Section three outlines the estimation approach and presents and describes the employed data. Section four delivers the estimation results for the full country sample. Section five delivers estimation results for highly developed and underdeveloped countries separately. The final section summarizes and draws some conclusions.

2 Related Literature

A few papers have studied the short-term effects of tropical storms. Strobl (2010) studies the growth impact of hurricanes in the Central American and Caribbean regions. In order to do so he applies a wind field model to hurricane data to construct an exogenous indicator of destructiveness. Strobl (2010) finds hurricanes to have a significantly negative effect on economic growth, which is, however, very short-lived. Strobl (2011) delivers a methodologically similar analysis for a highly developed country. In his study of the the growth impact of hurricanes on U.S. coastal counties he finds significantly negative effects of hurricanes. However, these effects do not turn out to be economically strong enough to be reflected in national economic growth rates. As both studies focus on certain regions it is somewhat unclear whether the results can be generalized. As Strobl (2010,2011), Felbermayr and Gröschl (2014) study the growth effects of natural disasters based on data on the physical strength of natural disasters. Using a dynamic panel regression approach for a sample of 108 countries and the time period of 1979 to 2010, the authors find strong empirical evidence in favor of the hypothesis that natural disasters affect short-term economic growth negatively. While Felbermayr and Gröschl (2014) study various disaster types, especially storms

turn out to have strong negative growth effects. These effects turn out to be especially pronounced in non-democratic countries and in countries with low degrees of trade and financial openness.

Interestingly enough, the pioneer paper by Skidmore and Toya (2002) for a long period of time was the only paper studying the long-term effects on natural disasters in general. The paper is based on the earlier discussed EM-DAT data and employs a cross-section approach by regressing the average real growth rate over the period of 1960 to 1990 on a set of control variables and the number of natural disasters occurring throughout the same period. The authors classify all disaster types into climatic and geologic disasters and find a statistically significant positive effect of climatic disasters on economic growth. The effect of geologic disasters tends to be negative, however is statistically insignificant in most cases. While the study by Skidmore and Toya was the first comprehensive study of the long-term growth effects of natural disasters, the analysis suffers from the earlier described endogeneity problem.

To the best of our knowledge the only existing study concerned with the long-term growth effects of storms is the paper already mentioned in the introduction by Hsiang and Jina (2014). The authors make use of panel data covering 110 countries and the time period of 1950 to 2008 and also control for spatial effects which might play a significant role in the case of hurricanes. As Felbermayr and Gröschl (2014) the authors make use of storm severity data from a meteorological database to prevent endogeneity problems. Hsiang and Jina (2014) find tropical storms to exert a systematically negative effect on economic growth, both in the short- and in the long-run.

3 Estimation Strategy and Data

3.1 Estimation Approach

Our empirical estimation strategy follows the basic idea of employing Barro Regressions (see e.g. Barro 1991, Mankiw, Romer and Weil 1992, and Islam 1995) and consists of estimating panel regressions of the type:

$$lnGDP_{t,i} - lnGDP_{t-1,i} = \alpha_i + \beta_t + \delta \cdot X_{t-1,i} + \epsilon_{t,i} \tag{1}$$

where $lnGDP_{t,i}$ is the natural logarithm of the per capita gross domestic product in country i at time t, α_i are country fixed effects controlling for countries differing institutions, cultures and geographies, β_t are time fixed effects, $X_{t-1,i}$ is a vector of one period lagged control variables and $\epsilon_{i,t}$ is the unexplained residual.[2] As it is usual in Barro Regressions we then add the variable of interest, an indicator of hurricane severity to

[2] As Felbermayr und Gröschl (2014) we thus estimate a twoway fixed effects model.

the estimation equation. The indicator $D_{t,i,k}$ measures hurricane severity in the actual and the k preceding years. Thus, the model we estimate is

$$lnGDP_{t,i} - lnGDP_{t-1,i} = \alpha_i + \beta_t + \gamma \cdot D_{t,i,k} + \delta \cdot X_{t-1,i} + \epsilon_{t,i} \tag{2}$$

In order to estimate the described model we need macroeconomic data (GDP, control variables) and an appropriate indicator of hurricane severity. We discuss the data sources and deliver some descriptive statistics on the employed data sources separately in the following.

3.2 Macroeconomic Data

As endogenous variable we need an adequate measure of the gross domestic product. We use Penn World Tables Version 8.0 (PWT 8.0) for this purpose (Feenstra, Inklaar and Timmer 2015) and construct our left hand variable from GDP per capita in constant prices of 2005 (RGDPNA). For the initial level of GDP per capita we use current GDP (output side, current PPP).

Table 1: Data Sources and Descriptive Statistics

Variable	Source	Mean	Std. Dev.	Min	Max
Growth of real GDP per capita (RGDPNA, 2005 const. prices)	PWT 8.0	0.035	0.069	-1.082	0.724
Log of current GDP, output side (current PPP)	PWT 8.0	10,006	2,106	3,965	16,257
Investment share of real GDP per capita (RGDPL, % of GDP)	PWT 8.0	0.198	0.114	0.006	1.396
Government share of real GDP per capita (RGDPL, % of GDP)	PWT 8.0	0.199	0.117	0.011	1.439
Net fertility rate (calculated)	WDI	3.816	1.579	1.065	7.795
Average years of total schooling, linear interpolated	Barro & Lee (2010)	5.134	3.051	0.024	12.726

We also need data on control variables which are typically used in growth regressions. The typically employed set of control variables is directly derived from neoclassical growth theory. Typically, measures of the initial level of GDP, the savings (or investment) rate, education, government consumption and the rate of population growth are considered. Data for the investment share of real GDP per capita and the government share of real GDP per capita were also extracted from Penn World Tables Version 8.0. The fertility rate comes from the World Development Indicators Database. As indicator for education we use the average years of total schooling (linear interpolated) as extracted from Barro and Lee (2010). Table 1 summarizes the data sources and delivers some descriptive statistics on the employed variables.

Altogether, our unbalanced panel dataset consists of data from 153 countries and covers the years of 1960 to 2002. The number of years included differs in between 12 and 43.

3.3 Best Track Data of Hurricanes

Besides macroeconomic data, we need an appropriate indicator of hurricane occurrence and destructiveness. Hurricanes are a specific and highly destructive form of storms.[3] They belong to the storm class of cyclones, which are defined as areas of low atmospheric pressure, characterized by rotating winds. As a consequence of the Coriolis effect, cyclones rotate counterclockwise in the Northern and clockwise in the Southern Hemisphere. Depending on their region of origin, cyclones are classified as tropical or extratropical. Tropical cyclones develop between 5 and 20 degrees latitude and thus over warm water. On the contrary, extratropical cyclones have cool central cores as they typically form between 30 and 70 degrees latitude in association with weather fronts. The two types of cyclones can have quite similar destructive effects, however, they differ in their source of energy and their structure. Tropical cyclones derive their energy from warm ocean water and heat of rising air which condenses and forms clouds. Extratropical cyclones derive their energy from the temperature difference of airmasses on both sides of a front.

According to the National Oceanic and Atmospheric Administration (NOAA) tropical cyclones with a maximum sustained wind of 38 mph (61 km/h) or less are called "tropical depressions". Whenever a tropical cyclone reaches winds of at least 39 mph (63 km/h) they are typically called "tropical storms". At this stage they are also assigned a name. If maximum sustained winds reach 74 mph (119 km/h), the cyclone is called a hurricane, whenever it developed in the North Atlantic Ocean, the Northeast Pacific Ocean east of the dateline or the South Pacific Ocean east of 160°E. In other regions the terms "typhoon" (Northwest Pacific Ocean west of the dateline), "severe tropical storm" (Southwest Pacific Ocean west of 160°E or Southeast Indian Ocean east of 90°E), and "severe cyclonic storm" (North Indian Ocean) are common. In the Southwest Indian Ocean the terminology sticks to the simple term "tropical cyclone".

Hurricanes (or more general tropical cyclones) are further classified according to their wind speed. This is often done by employing the Saffir Simpson Scale (see Table 2).[4] The Saffir Simpson Hurricane Wind Scale is a 1 to 5 rating based on the hurricane's intensity. This scale only addresses the wind speed and does not take into account the potential for other hurricane-related impacts such as storm surge and rainfall-induced floods. Earlier versions of this scale, known as the "Saffir Simpson Hurricane Scale", also incorporated these categories, however, often led to quite subjective and sometimes implausible categorizations of occurring storms. In order to reduce public confusion and to provide a more scientifically defensible scale, the storm surge ranges, flooding impact and central pressure statements were removed from the Saffir Simpson Scale

[3] The following expositions are primarily based on Keller and DeVecchio (2012).

[4] The scale is named after its inventors, the wind engineer Herb Saffir and the meteorologist Bob Simpson.

and only peak winds are now employed.

Table 2: Saffir Simpson Hurricane Wind Scale

Category	Sustained Winds	Types of Damage Due to Hurricane Winds
1	74-95 mph 64-82 kt 119-153 km/h	Very dangerous winds will produce some damage: Well-constructed frame homes could have damage to roof, shingles, vinyl siding and gutters. Large branches of trees will snap and shallowly rooted trees may be toppled. Extensive damage to power lines and poles likely will result in power outages that could last a few to several days.
2	96-110 mph 83-95 kt 154-177 km/h	Extremely dangerous winds will cause extensive damage: Well-constructed frame homes could sustain major roof and siding damage. Many shallowly rooted trees will be snapped or uprooted and block numerous roads. Near-total power loss is expected with outages that could last from several days to weeks.
3	111-129 mph 96-112 kt 178-208 km/h	Devastating damage will occur: Well-built framed homes may incur major damage or removal of roof decking and gable ends. Many trees will be snapped or uprooted, blocking numerous roads. Electricity and water will be unavailable for several days to weeks after the storm passes.
4	130-156 mph 113-136 kt 209-251 km/h	Catastrophic damage will occur: Well-built framed homes can sustain severe damage with loss of most of the roof structure and/or some exterior walls. Most trees will be snapped or uprooted and power poles downed. Fallen trees and power poles will isolate residential areas. Power outages will last weeks to possibly months. Most of the area will be uninhabitable for weeks or months.
5	157 mph or higher 137 kt or higher 252 km/h or higher	Catastrophic damage will occur: A high percentage of framed homes will be destroyed, with total roof failure and wall collapse. Fallen trees and power poles will isolate residential areas. Power outages will last for weeks to possibly or higher months. Most of the area will be uninhabitable for weeks or months.

Source: http://www.nhc.noaa.gov/aboutsshws.php

The hurricane indicator, we employ in our empirical analysis, is based on data from a meteorological database: the Best Track Dataset of tropical cyclones provided jointly by the National Oceanic and Atmospheric Administration (NOAA), the Tropical Prediction Center (Atlantic and eastern North Pacific hurricanes) and the Oceanography Center / Joint Typhoon Warning Center (Indian Ocean, western North Pacific, and Oceania hurricanes).[5] The advantage of this database is its worldwide coverage. The Best Track dataset provides data on the position of tropical cyclone centers in 6-hourly intervals[6] in its geographic coordinates, the measured maximal sustained wind speed in knots,[7] central surface pressure data in millibar and the Saffir Simpson Hurricane Wind Scale rating of the referring storm interval. The data is collected post-event from different sources like reconnaissance aircraft, ships and weather satellites.

Most of the time, hurricanes are located over the open sea. While tropical cyclones might cause some damage there, e.g. at oil platforms or ships, the referring storm periods are a thread to life and/or wealth for only a minimal fraction of the population. We therefore concentrate on storm periods occurring over land masses. Most of these storm periods are located in coastal areas. This is due to the fact that tropical cyclones

[5]The dataset was downloaded from the Unisys Weather Hurricane Data Archive at: http://weather.unisys.com/hurricane/index.php. For our purposes we used the tracking information files for each single hurricane provided in the annual storm tracking data.

[6]The data is recorded on a daily basis at 12am, 6am, 12pm, and 6 pm.

[7]The database contains the average maximum sustained wind speed at 10 metres above the earth's surface over a one minute time span anywhere within the tropical cyclone.

rapidly diminish when a cyclone's eye passes land masses. Atop land masses a storm lacks moisture and heat provided by the ocean. As a consequence it quickly loses power and starts diminishing. However, as the destructive power of a tropical cyclone goes well beyond a cyclone's center we follow Yang's (2005) proposal to include all 6-hourly storm intervals with a Saffir-Simpson grading whose centers pass a country's borders up to a 160 kilometer distance (for a graphical illustration see Figure 1). This buffer zone might be justified by the typical structure of tropical cyclones. Its strongest winds are located in the eyewall, a ring of tall thunderstorms located around the cyclone's eye. The eye is the calmest part of the tropical cyclone with a typical diameter of in between 32 and 64 kilometers. Around the eyewall and arranged like a spiral, there are curved rainbands producing heavy rain, wind and tornadoes. The destructive winds and rains of a tropical cyclone affect a wide area. Hurricane winds may extend to more than 242 kilometers from the eye of a large tropical cyclone. Because this extension may vary considerably from case to case, a cautious buffer of 160 kilometers seems to be reasonable.

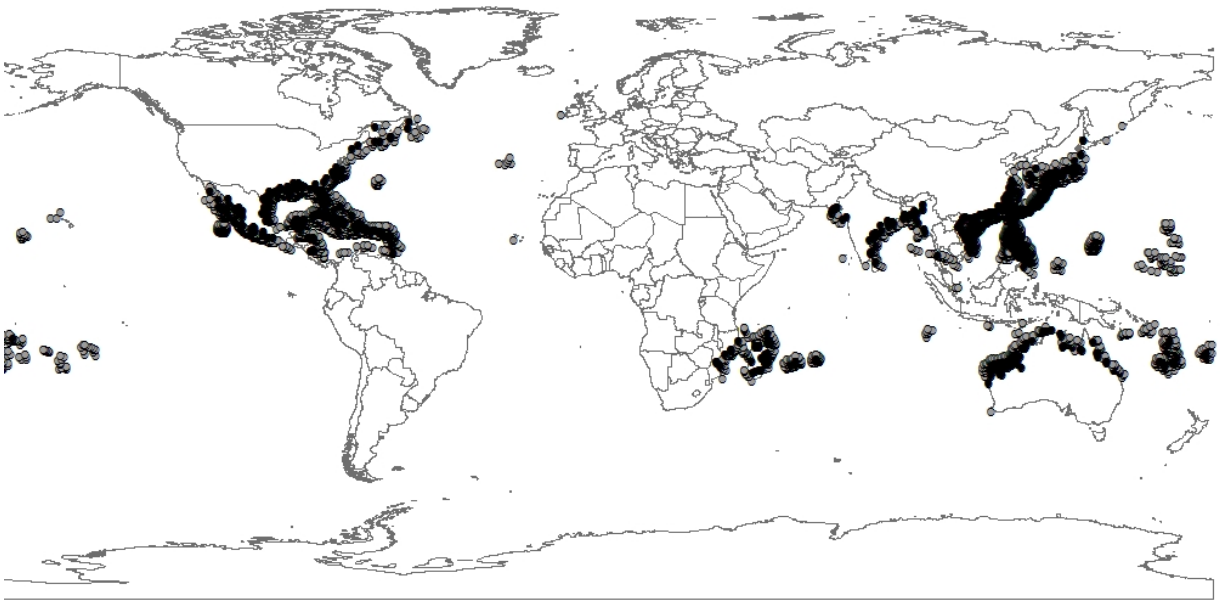

Figure 1: 6-hourly Storm Periods

Using the described Best Track Dataset we construct three different hurricane indicators: The first indicator (*SNO*) is the annual sum of all six-hourly storm intervals with a Saffir-Simpson grading whose centers pass a country's borders up to a 160 kilometer distance. Note that this indicator is not a pure frequency indicator of hurricanes, as it bases on the number of six-hourly storm periods. Thus, storms which are located

over landmasses for longer periods of time have a higher impact on the indicator than quickly decaying hurricanes. Moreover, more severe hurricanes are also more likely to exist for longer periods of time. For reasons of simplicity, we nevertheless refer to this indicator as "frequency indicator" in the following.

The second hurricane indicator, we calculate for our empirical analysis, also incorporates storm severity. This indicator, we refer to as "Saffir Simpson severity indicator" in the following (*SSSS*), is defined as the annual sum of Saffir-Simpson gradings of all six-hourly storm intervals whose centers pass a country's borders up to a 160 kilometer distance.

As an alternative, we calculate a severity indicator, which is based on maximum wind speed. Emanuel (2005) developed a method which allows representing the destructiveness of a tropical cyclone on the basis of its maximal sustained wind speed. He proposes a simplified version of the Power Dissipation Index (PDI) which was originally introduced by Bister and Emanuel (1998). It measures the total frictional dissipation of kinetic energy in the boundary layer of the tropical cyclone over the whole lifetime of the storm, whereas the hurricanes boundary layer is the lowest layer where the winds are influenced by the friction of the earth's surface and the objects on it. The simplified version of the PDI is computed as the integral over the storm lifetime of the cubic maximal sustained wind speed. For our purpose we compute the indicator as the annual sum of the cubed maximum sustained wind speed of all six-hourly storm intervals whose centers pass a country's borders up to a 160 kilometer distance. We refer to this indicator as "wind speed severity indicator" in the following (*SWIND*).

As we are interested in the long term growth effects of tropical storms, we average the three described storm indicators over various periods. Our hurricane indicators $D_{t,i,k}$ at time t are defined as the average of the indicator values over the actual and the k preceding years in country i (per mio. sqkm). The utilization of this sort of indicator allows us identifying whether hurricanes affect economic growth only in the very short-run (in this case only the versions of the indicator including the directly preceding years should turn out to be significant) or whether the medium and long-run storm history is (also) relevant.

4 Full Sample Estimation Results

We start out our empirical analysis with estimating the baseline growth model from equation 1 for the whole country sample. The results for the twoway fixed effects model are shown in the columns 2 to 4 of Table 3. For the initial level of GDP, the savings rate and fertility the coefficients are significantly different from zero. Moreover, they have the expected sign. While the coefficients for education and the government share also have the expected sign, the estimated coefficients are not significantly different

from zero. As the Wooldridge Test indicates, the estimated twoway fixed effects model suffers from autocorrelated residuals. One way of dealing with this problem is to report HAC standard errors (Newey and West 1987), as we do in Table 3. A second way of dealing with autocorrelated residuals is to estimate a dynamic version of the twoway fixed effects model. We show the referring estimation results in columns 5 to 7 of Table 3. The estimated coefficients remain both qualitatively and quantitatively very similar. As the Wooldridge Test indicates, the inclusion of the first lag of the left hand variable solves the autocorrelation problem of the residuals in a satisfactory manner.

Table 3: Baseline Estimation Results: Determinants of Economic Growth

	Twoway FE model			Dynamic twoway FE model		
	coefficient	**s.e.**	**p-value**	**coefficient**	**s.e.**	**p-value**
Control variables:						
lag(lncgdpo, 1)	-0.034***	0.008	0.000	-0.034***	0.008	0.000
lag(lnis, 1)	0.011***	0.003	0.000	0.006**	0.003	0.048
lag(lneduavg2i, 1)	0.002	0.003	0.409	0.003	0.003	0.192
lag(lngs, 1)	-0.003	0.003	0.281	-0.001	0.003	0.636
lag(lnfertn, 1)	-0.019**	0.009	0.032	-0.021***	0.008	0.007
lag(wr gdppwtna, 1)				0.232***	0.030	0.000
Regression statistics:						
no. of observations	5,496			5,448		
no. of countries	130			130		
F-Value	33.707***			78.767***		
adj. R-square	0.030			0.080		
Wooldridge test:	$\chi^2 = 28.926, p = 0.000$			$\chi^2 = 0.004, p = 0.952$		

Notes: Dependent variable: wr gdppwtna. Heteroscedasticity and autocorrelation-corrected (HAC) standard errors reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% level. Fixed effects included, but not reported. We report the results of the Wooldridge test for serial correlation in FE panels.

In the next step we estimate the model 2 which is extended by the three discussed hurricane indicators. We estimate the model for different values of k. Thus we calculate past hurricane severity over different time horizons, ranking from $k = 0$ to $k = 25$. Due to space restrictions we refrain from reporting the complete estimation results, but show the estimated coefficients and the referring p-values for alternative specifications of k. To rule out that the results depend on the chosen solution of the earlier described autocorrelation problem of the model residuals we estimate the model without and with lagged dependent variable. We always report HAC standard errors.

Figure 2 shows the estimation results for the model without lagged dependent variable. The frequency indicator delivers no evidence in favor of a systematic effect of hurricanes on economic growth. However, the usage of the wind speed or the Saffir Simpson severity indicator delivers a different picture. For values exceeding $k = 10$ the

estimated coefficients are negative and significant on at least the 10% significance level in most cases.

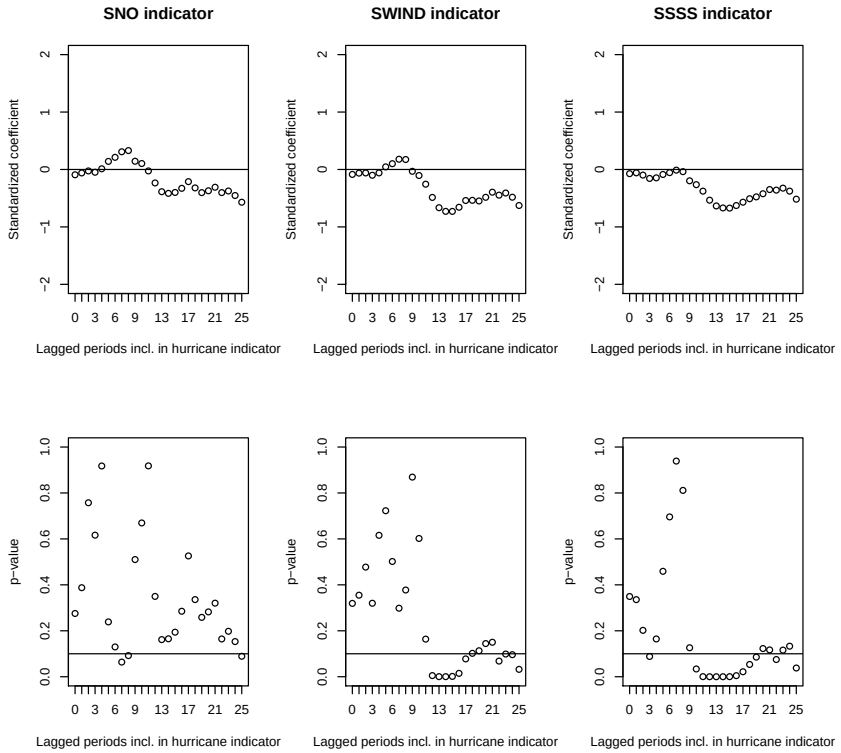

Figure 2: Effect of Disaster Indicators on Economic Growth (Twoway FE Panel Regression)

Figure 3 shows the estimation results for the dynamic version of the model. In general, the results are similar, however, for the Saffir Simpson severity indicator the significance levels turn out to be systematically higher.

Altogether we might conclude that we find a systematically negative effect of hurricanes on economic growth in the whole sample when (i) including at least the 10 preceding years into the hurricane indicator and (ii) employing one of the two described severity indicators rather than the frequency indicator.

5 Estimation Results for Developed and Underdeveloped Countries

We now turn to the question whether the identified long term growth effects of hurricanes in the full country sample are driven by a special country group. As Skidmore and Toya (2007) have argued, poor countries can protect much worse against the effects of natural disasters in general. In order to study this issue we divide our sample in two subsamples of comparatively rich and poor countries, based on the classification of the

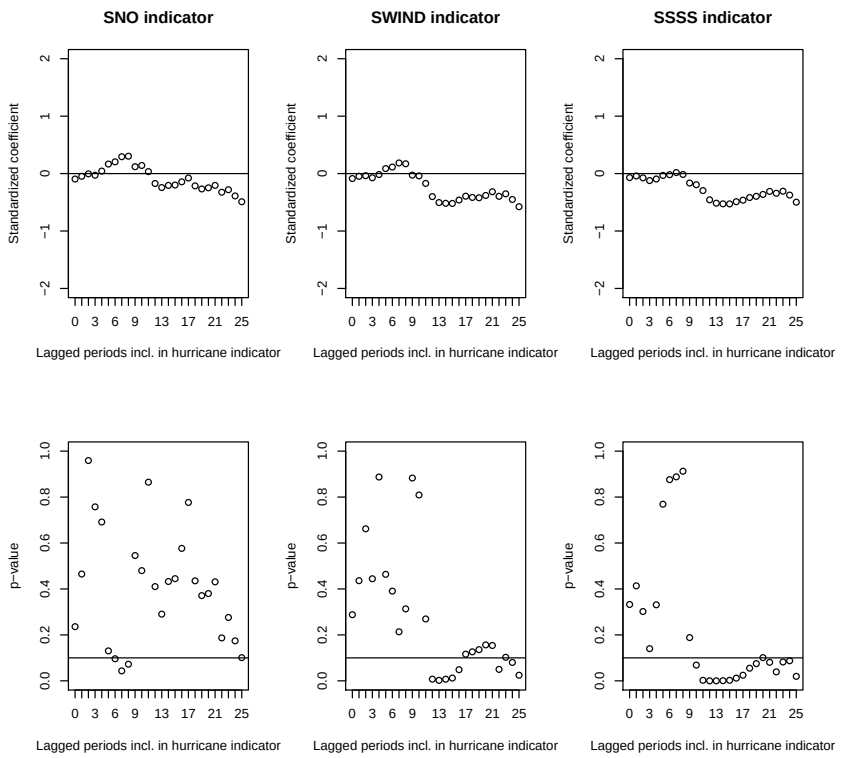

Figure 3: Effect of Disaster Indicators on Economic Growth (Dynamic Twoway FE Panel Regression)

World Bank. The group of rich countries consists of all high and upper middle income countries (illustrated in black color) whereas the group of poor countries (illustrated in red color) includes the lower middle and low income countries. The estimation results are shown in Figures 4 and 5.

Both figures clearly indicate that the negative growth effects of hurricanes are driven by the group of comparatively poor countries. Regardless of which hurricane indicator is employed, we find significantly negative growth effects of tropical storms especially in the sample of poor countries. When using at least 9 preceding periods, almost all estimated coefficients are negative. Compared to the sample of rich countries the effects are much more pronounced. Moreover, the estimated coefficients for the poor countries turn out to be much higher than those reported in the estimations of the whole country sample. Only very rarely, we find significant effects for the high income countries.

6 Conclusions

Based on truly exogenous storm indicators, derived from a meteorological database, we show that the growth effects of tropical storms go well beyond the short-term perspective. Based on the full country sample we are able to identify negative long term growth consequences of tropical storms in the full country sample. However,

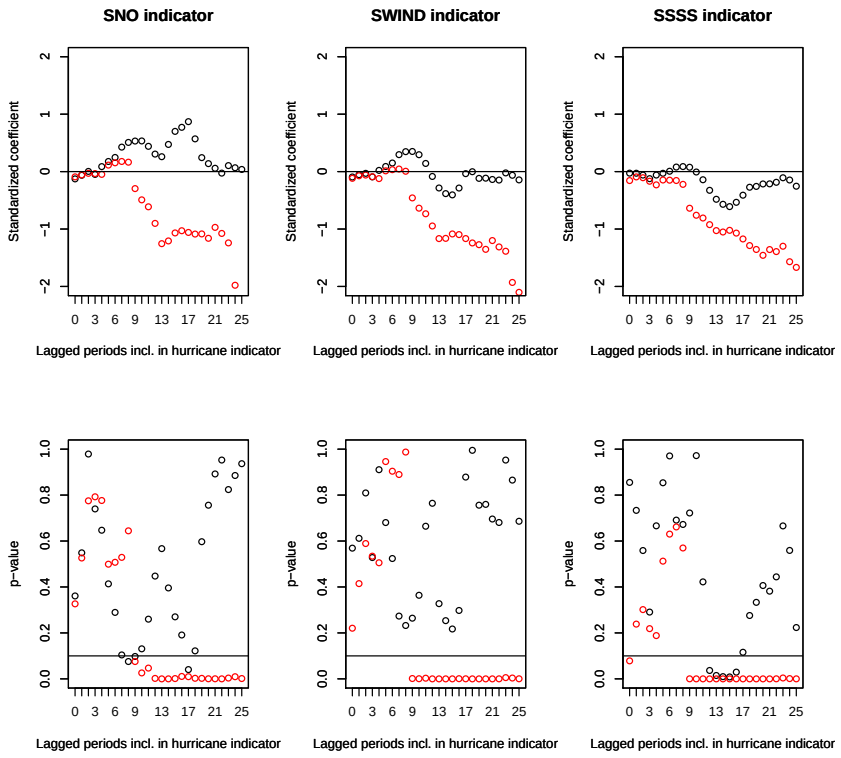

Figure 4: Effect of Disaster Indicators on Economic Growth in Rich and Poor Countries (Twoway FE Panel Regression)

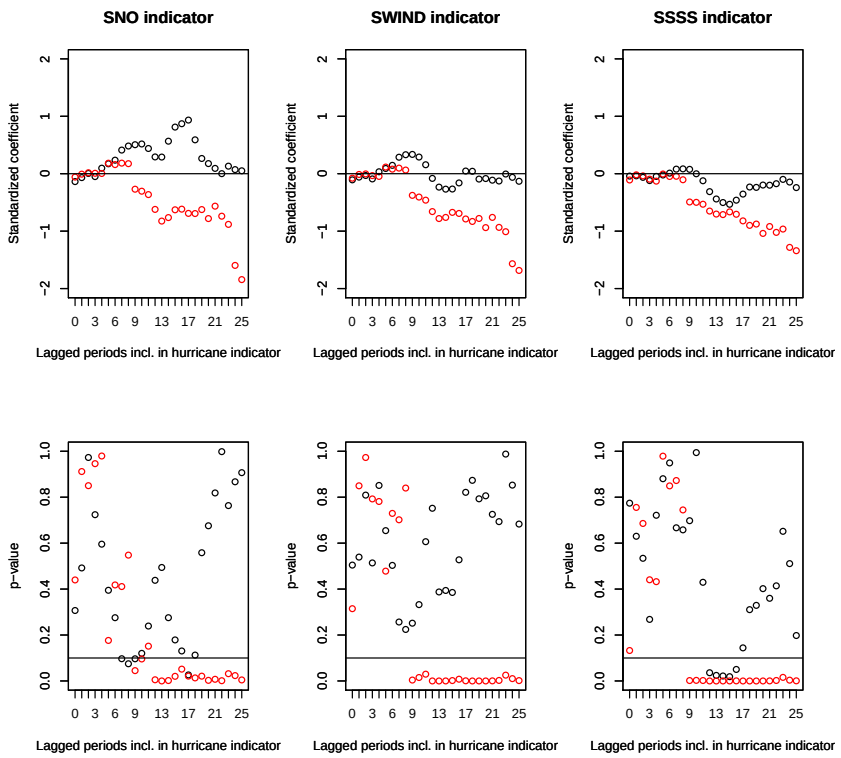

Figure 5: Effect of Disaster Indicators on Economic Growth in Rich and Poor Countries (Dynamic twoway FE Panel Regression)

these effects primarily occur in comparatively poor countries for which protective measures are typically too costly to be implemented. Thus, hurricanes might contribute to explaining why numerous less developed countries fail to catch up with the more developed countries. In order to allow these countries to escape from this "poverty trap", external help is essential.

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DO NATURAL DISASTERS AFFECT INDIVIDUAL SAVING? EVIDENCE FROM A NATURAL EXPERIMENT IN A HIGHLY DEVELOPED COUNTRY

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Abstract

While various empirical studies have found negative growth-effects of natural disasters, little is yet known about the microeconomic channels through which disasters might affect short- and especially long-term growth. This paper contributes to filling this gap in the literature by studying how natural disasters affect individual saving decisions. This study makes use of a natural experiment created by the European Flood of August 2002. Using micro data from the German Socio-Economic Panel that we combine with geographic flood data, we compare the savings behavior of affected and non-affected individuals by using a difference-in-differences approach. Our empirical results indicate that natural disasters depress individual saving decisions, which might be the consequence of a Samaritan`s Dilemma.

JEL code: Q54, D14, O16, H84

Keywords: natural disasters, floods, growth, saving behavior, natural experiment, difference-in-differences approach

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1. Introduction

Climate change is often seen as one of the most challenging problems of our time. According to the United Nations Human Development Report 2007/2008, "In the long run climate change is a massive threat to human development [...]". Against this background it does not come as a surprise that many scientific disciplines are dealing with the causes and consequences of climate change. This also holds true for economics, as climate-related economic research has intensified considerably throughout the last decades. Early research focused on the question of how regulation might contribute to a slowdown of carbon-dioxide emissions. However, more recently the focus has changed towards forecasting the likely economic consequences of climate change and to appropriate adaptation policies.

One consequence of climate change is the increased frequency and/or severity of certain types of natural disasters and extreme weather events (UNISDR 2009, Thomas 2014). Against this backdrop, there has been an increasing interest in the question of whether and how natural disasters affect economic growth. Since the first systematic analysis of this question was conducted by Skidmore and Toya (2002), a growing body of empirical literature studying the growth effects of natural disasters has evolved. Most of the existing empirical evidence concerns the short-term effects of natural disasters (see, e.g., Kahn 2005, Anbarci et al. 2005, Bluedorn 2005, Raddatz 2007, Loayza et al. 2012, Noy 2009, Mechler 2009, Hochrainer 2009 and Strobl 2012). The existing body of research tends to find negative short-term growth effects of natural disasters. These negative short-term effects are more pronounced in less developed than in high income countries. As Noy (2009) argues, this might be due to financial constraints in reconstruction, less developed insurance markets, and limited possibilities to run counter-cyclical fiscal policies. Much less empirical evidence is available on the long-term growth effects of natural disasters. In their cross-sectional study of 89 countries, the pioneering paper by Skidmore and Toya (2002) finds different results for climatic and geologic disasters. Whereas the frequency of climatic natural disasters turns out to have a positive effect on economic growth, geologic disasters tend to have a negative although insignificant impact on economic growth. However, most subsequent studies have found a negative impact of natural disasters on long-run growth (see e.g. Noy and Nualsri 2007, Raddatz 2009, Felbermayr and Gröschl 2014, and Hsiang and Jina 2014).

Broadly summarized, one might conclude that natural disasters, at least large ones, tend to affect economic growth negatively, both in the short- and long-run, although the strength of the effect depends on country characteristics and the type of disaster. Interestingly enough, the existing empirical literature remains relatively vague with respect to the specific channels through which natural disasters might affect long-run economic growth. Only a few papers have engaged in attempts at uncovering these channels.[1]

In this paper we aim to shed additional light on one specific channel through which natural disasters might affect economic growth: saving behavior. The savings rate is well-known to be a decisive factor in determining per-capita income in macroeconomic models of economic growth in closed economies. In open economies, the role of domestic saving for economic growth is less clear, as domestic investments can also be financed by foreign savings. However, there are reasonable theoretical arguments for why domestic saving is also crucial in open economies. Dooley, Folkerts-Landau and Garber (2004) argue that poor and instable countries in particular might transfer domestic savings to countries of possible investors, thereby making expropriations of foreign investors' capital less likely. Thus, the transfer of domestic savings takes on the role of collateral, which encourages foreign investments and contributes to better economic development. In a similar vein, however, based on a well-defined theoretical model, Aghion, Comin and Howitt (2006) argue that domestic savings play an important role in relatively poor countries that employ production technologies far away from the actual frontier techniques. In these countries, catching up to developed countries requires a joint venture between a foreign investor who is familiar with the frontier technology and a domestic entrepreneur who is familiar with the local conditions. In this scenario, domestic savings are necessary to mitigate the agency problem which would otherwise deter the foreign investor from joining this project. The empirical evidence that Aghion, Comin and Howitt (2006) present supports the relevance of this line of argument. Moreover, most of the existing panel studies on the determinants of economic growth suggest that domestic savings have a positive impact on economic growth (see, e.g. Barro 1991, Mankiw, Romer and Weil (1992) or Islam 1995).

In summary, we might conclude that whenever natural disasters have a systematic influence on domestic savings behavior, medium- or even long-term economic growth will also be

[1] We summarize the related literature in section two of this paper.

affected. However, the effect of natural disasters on domestic savings is ex-ante ambiguous. In principle natural disasters can affect individual saving behavior in different ways and through different channels.

Saving is typically seen as a means of consumption smoothing. Naturally, the amount of saving will increase with a corresponding increase in life expectation. Whenever natural disasters make individuals believe that life expectations decrease, this might increase consumption and depress saving. However, the theory of precautionary saving argues that saving does not only serve to spread income over the life cycle, but might also serve as insurance against uncertain events (Lusardi 1998). In this context, Roson et al. (2005) argue that individuals might react to natural disasters by increasing their savings. Based on a theoretical model of constant absolute risk aversion, Freeman, Keen and Mani (2003) show that the optimal amount of precautionary saving depends positively on expected loss, and thus on both the disaster probability and disaster loss. Natural disasters might increase expected losses and thus increase precautionary saving. This effect should be the more pronounced in more risk-averse individuals (Fuchs-Schündeln and Schündeln 2005). However, it is also possible that precautionary saving is reduced as a consequence of natural disasters. Often individuals who have suffered from catastrophic losses are supported or even compensated by state institutions, private donations, or international aid. All these forms of support decrease the incentives for accumulating one's own precautionary savings. Finally, individuals might be forced to reduce saving for a certain period of time in response to natural disasters, due to increases in expenditures (e.g., for repairs or replacements) or negative income shocks.

In order to further investigate the effects of natural disasters on saving behavior, we study whether the occurrence of a large natural disaster (i.e., the flood of August 2002 in central Europe) affected subsequent individual saving behavior in the flooded region. We base our study on micro-level data from the German Socio-Economic-Panel (SOEP), thereby focusing on those panel members who lived in Saxony, which was the German state that was the most affected by the flood catastrophe.[2] Using geo-referenced maps of the flood, we identify two groups of individuals. The first group of individuals lived in regions of Saxony that were unaffected by the flood; they serve as our control group. The second group lived inside the

[2] The data used comes from the Socio-Economic Panel (SOEP), data for years 1984-2012, version 29, SOEP, 2013, doi:10.5684/soep.v29.

flooded regions and make up our treatment group. We then apply a difference-in-differences approach to analyze the impact of the 2002 flood on individual saving behavior.[3] We find that the flood caused a significant reduction in individual savings. We also show that this finding cannot be explained by income effects alone, and discuss the potential driving forces behind our results.

The remainder of the paper is organized as follows. In the second section, we briefly summarize the related empirical literature. The third section gives a brief overview on the August 2002 flood catastrophe in central Europe, with a special emphasis on Saxony, introduces the dataset, and explains our estimation strategy. In section four, we study the effect of the flood catastrophe on individual saving volume, and also distinguish between the extensive and intensive margin of the saving decision. Section five examines the potential income effects and analyzes the individual savings rates. Section six delivers additional robustness checks. The final section, we summarize our main results and offer concluding remarks.

2. Related Literature

In the standard neoclassical growth model, a natural disaster destroying parts of an economy's capital stock and has a negative short-term impact on per-capita Gross Domestic Product (GDP). Thus, in the very short-term perspective, natural disasters should negatively affect the growth rate. As the economy returns to its long-term steady state, the intermediate growth rate must exceed the long-term trend. In the long-run, the growth rate should remain unaffected by the disaster as the economy has returned to its steady state.

Natural disasters might have an influence on long-run economic growth whenever one of the key variables (i.e., those assumed to be exogenous in the standard neoclassical growth model) changes as a result of a natural disaster. The most important factors determining steady state per-capita GDP are the savings rate (i.e., and thus investments), population growth, human

[3] Bechtel and Hainmueller (2011) use the August 2002 flood to analyze the impact of national aid flows on voter gratitude. Using data on electoral districts, they apply a difference-in-differences analysis to estimate the effect of disaster aid on national election outcomes. In contrast to our paper, they did not use geo-referenced information on floods, but aggregated data on flooding at the level of electoral districts. Regarding flood assistance, they assume that every district that was affected by the flood received disaster aid. They conclude that flood aid had a positive impact on the voter share of the incumbent party in the preceding election.

capital accumulation, and the rate of technical progress. However, to date the empirical literature has rarely studied whether and how the occurrence of natural disasters influences these factors. To the best of our knowledge, the only study that is explicitly concerned with the effects of natural disasters on these growth factors is the early study by Skidmore and Toya (2002). The authors detected no significant effect of disaster risk (i.e., measured by the average rate of disasters which occurred throughout the sample period of 1960-1990) on the growth of physical capital (and thus saving). The effect of natural disasters on human capital growth and total factor productivity turns out to depend on the type of natural disaster. While the effect of geologic disasters is negative and insignificant, the effect of climatic disasters on both human capital accumulation and total factor productivity is positive and significant. The authors therefore conclude that climatic disasters have a positive impact on long-run economic growth, as climatic disasters provide the opportunity to update capital stock and adapt new technologies. However, subsequent literature has found little support for this hypothesis that climatic natural disasters have a positive long-term growth effect.

Based on a life cycle expected utility model, Skidmore (2001) shows that saving should generally increase as a result of rising expected future losses from natural disasters. While this result does not hold when perfect insurance is available, Skidmore (2001) argues that even in highly developed countries, disaster insurance is often unavailable due to the combination of the low likelihood of disaster occurrence and the enormous damages to be covered in the case of disaster events. Based on a very small dataset consisting of 15 highly developed countries, Skidmore (2001) found that the more a country is prone to natural disasters, the higher the aggregate saves rate.

In order to investigate how natural disasters might influence long-run growth, it is useful to study behavioral responses to disasters at the microeconomic level. Although the existing empirical evidence is relatively scarce, recently a number of papers have studied this issue, although rarely in a growth context. Sawada and Shimizutani (2008) find that post-disaster consumption behavior patterns after the Kobe earthquake depend strongly on individual borrowing constraints. In an attempt to quantify the costs of floods in European countries, Luechinger and Raschky (2009) find that individual happiness is negatively affected by flood disasters. Berlemann (2014) finds that global hurricanes only depress happiness in the short-run. However, hurricane risk turns out to have a strong negative impact on life satisfaction.

Page et al. (2014) find that the Brisbane flood of 2011 had a significant effect on individual risk seeking behavior whenever an individual suffered a large loss in wealth. Cameron and Shah (2013) conducted several field experiments with individuals affected by disasters in rural Indonesia and find them to be more risk adverse. Taken together, this evidence suggests that natural disasters might induce behavioral responses.

3. Background, Data and Methodology

In our analysis of behavioral responses to natural disasters, we study whether and how individuals adjusted their saving behavior in response to a severe flood that occurred in central Europe in summer 2002. Before we turn to the empirical analysis, we first summarize the main facts about the flood catastrophe. We then turn to a description of the dataset and explain the basic strategy used to identify individuals who were affected by the flood. The section ends with an introduction of the employed empirical methodology.

3.1 The August 2002 Flood in Saxony

In July and the beginning of August 2002, central Europe experienced multiple waves of heavy rainfall and thunderstorms. Several watercourses exhibited increased gauge stages and the soil was saturated with water in many parts of Saxony, Bavaria, the Czech Republic, and Austria (Löpmeier 2003). The first floods in these areas occurred between August 7 and 11, as water houses were only able to drain off above ground (GWS 2007). In the early hours of August 12, the storm front *Ilse* crossed the Czech Republic and moved towards Saxony. The overall meteorological situation in Europe during that time and the orographic conditions in Saxony caused extreme rain as the storm front *Ilse* completely unloaded its waters above eastern Germany. In the Ore Mountains, which are close to the Czech boarder, official measures reported 312 liters of water per square meter within 24 hours (Rudolf and Rapp 2003). This all-time German record exceeded historical precipitation levels by a factor of four. In other central European regions, *Ilse* dropped between 80 and 167 liters of water per square meter in a 24 hour period. In many affected regions, the water masses caused massive direct damage.

In Saxony, the water masses caused destruction through various channels. First, small watercourses in the Ore Mountains flooded and caused destruction on their way down to the Elbe River. Much of the reported damage was caused by these tributaries that are normally rather small. Second, many of the water reservoirs located in the Ore Mountains already exhibited increased gauge stages. Traditionally the reservoirs had two functions, drinking water storage and flood prevention for the Elbe valley. In late July, many of the reservoirs had gauge stages close to maximum in order to provide ample fresh and drinking water for the summer season. When the somewhat unexpected heavy rain period started, emergency drainages became necessary in various reservoirs to prevent bursting dams. As a consequence of one of these emergency drainages, the Weißeritz stream, which is normally a small watercourse in the Ore Mountains, became a torrential river within a matter of minutes and caused massive destruction in several villages including the medium-sized city of Freital and Saxony's capital Dresden, where the water flooded the main station and substantial parts of the city center. Third, the specific orographic constellation of the region from Prague to Dresden makes the Elbe River the only significant drainage for increased water houses. Thus, the heavy rainfall at the beginning of August steadily increased the gauge level of the Elbe River. Finally, several flood waves from the Czech Republic made their way down the Elbe River and reached eastern Germany after this heavy rain period of August 11 and 12. The already high gauge stages of the Elbe thus increased even further, thereby causing severe damage to many settlement areas close to the Elbe River.

Even though the Elbe River is by far the largest watercourse that was affected by the heavy rain, the flood catastrophe was not restricted to its surrounding areas. As mentioned earlier, other areas such as those close to the Mulde River were also affected, and severe damage was often caused by small tributaries such as the Weißeritz. Consequently, the flood affected many distinct parts of Saxony.

For Germany as a whole, the Center for Research on the Epidemiology of Disasters (CRED) reports that 330,108 people were affected and the damage totaled $11.6 billion. In these two dimensions, the 2002 flood is Germany's most severe natural disaster recorded in the CRED database.

3.2 Household Data

For our empirical study, we used the German Socio-Economic Panel (SOEP), a panel dataset on German households.[4] The SOEP is a representative annual panel survey which started in 1984 in West Germany, and has included the areas that formerly comprised East Germany since German Reunification in 1990. The survey contains roughly 150 questions that allow researchers to extract information on the socio-economic infrastructure of the included households. Among other variables, the survey includes data such as individual wealth, income, employment, and health status. All household members above the age of 17 are personally interviewed. In addition to a personal interview, the head of the household answers an additional household questionnaire.[5]

All household variables that were used in the empirical estimations were taken from the SOEP. To identify those households that lived in flooded areas, we made use of anonymized regional information on the residences of SOEP respondents.[6] This data is considered as highly sensitive and is subject to particular data protection regulations. We refrain from describing all variables here, but a complete description of the employed variables can be found in Table A1. Instead, we focus on describing those variables which served as dependent variables in our empirical analyses. Our analysis of individual saving behavior is based on the answers to the question:

"Do you usually have an amount of money left over at the end of the month that you can save for larger purchases, emergency expenses or to acquire wealth? If yes, how much?"

The head of the household answers this question by reporting aggregate monthly household savings. In the subsequent empirical analysis we study individual saving behavior.[7] Thus, whenever households consist of more than one person we have to make an appropriate assumption how aggregate saving can be attributed to the individual household members. It seems to be reasonable to assume that individual saving is proportional to individual income,

[4] The SOEP data can be obtained from the SOEP Research Center located at the German Institute for Economic Research (DIW) in Berlin.
[5] For a more detailed description of the SOEP survey, see Wagner et al. (2007).
[6] Section 3.3 contains a detailed description of the regional data used to identify flooded regions and how it is matched to SOEP households.
[7] The results of our empirical analysis remain qualitatively unchanged when conducting the analysis on the household level, as we will show in the robustness section 6.

which is measured as the sum of revenues from all recorded sources, including wages, social benefits, rents and any other sources of income received regularly. We then attribute the household saving volume to the household members based on their individual share in total household income.[8] As we are interested in real rather than in nominal savings, we deflate savings by the German consumer price index and code the result as the variable S.[9]

For the analysis of saving behavior at the extensive margin, we additionally construct the dummy variable S_E, which takes the value of one whenever a respondent saves and zero otherwise:

$$S_E = \begin{cases} 1 | S > 0 \\ 0 | S = 0 \end{cases}$$

Finally, in order to study the saving decision at the intensive margin, we construct the variable S_I. This variable is only defined for individuals in households which declare they save a positive amount of money, i.e.:

$$S_I = S \mid S > 0$$

3.3 Definition of Treatment and Control Group using Flood Data

In 2002, the SOEP contained 23,892 people living in 12,605 households. Of these, 1,678 people (or 860 households) lived in Saxony. As Saxony was the German state most heavily affected by the August 2002 flood, we concentrate our analysis on SOEP members living in Saxony when the August 2002 flood occurred. Since the financial freedom of children and adolescents is rather limited, we exclude all respondents younger than 18 from our analysis. In our empirical analysis, we are interested in comparing savings behavior before and after the flood occurred. We therefore exclude all respondents who were interviewed in 2002 (i.e., after the flood occurred in early August).[10] Hence, the remaining 1285 respondents interviewed in 2002 compose our pre-disaster observations.

[8] All subsequently shown empirical results remain qualitatively unchanged when attributing the same share of savings to each household member as a more conservative variant of the applied procedure.

[9] We make use of the consumer price index (code 61111-0001) published by the German Statistical Office. Savings are expressed in € values as of year 2000.

[10] As the SOEP questionnaire is primarily carried out in the first half of the year, very few observations were excluded for this reason.

A crucial issue in our empirical analysis is the identification of those SOEP respondents who lived in the flooded area and were therefore strongly affected by the 2002 flood. Not surprisingly, the SOEP dataset does not contain a variable or question that pertains to this issue. However, by applying a three-step procedure which we will describe in detail, we are nevertheless able to identify Saxon SOEP respondents who lived in the area flooded in August 2002. In the first step, we collect detailed geographic data on the flood impact in Saxony. For this purpose, we employ a combination of two flood maps. The first map was constructed by the Saxon State Office for Environment, Agriculture and Geology on the basis of aerial photography and hydraulic computations. The map was refined and updated various times; we use the version dated November 2007. As this first map excludes the city of Dresden (i.e., one of the most heavily affected regions in Saxony), we combined this map with a flood map provided by the City of Dresden's Department for Environmental Protection. After merging the two maps, we attained one coherent flood map covering the whole state of Saxony.[11] The combined map contains about 220 watercourses. Some 2,800 kilometers, or 11.2 percent of Saxony's watercourses, were affected.[12] The total flooded area amounts to about 40,000 hectares.[13] Roughly 20 percent of this area is classified as settlement or infrastructural area. Figure 1 shows a graphical representation of the employed combined flood map. Dark areas were flooded throughout August 2002 while areas marked in light gray indicate watercourses. The shaded areas depict settlements.

In the second step, we localize the SOEP households within Saxony geography. Although the standard SOEP dataset provides only information on the state level in order to protect respondent's data privacy, more detailed information is available at the SOEP Research Data Center in Berlin.[14] The available geographical units comprise inter alia, official municipality keys, postal codes, and Microm neighborhood data. All of these geographical identifiers have been available since 2000, at the latest. As the Microm neighborhood data contains the most

[11] The creation of the flood map is based on maps with a scale of 1:10,000 (in cm) and the official topographic map TK 10. For validity checks, more highly scaled maps (e.g., 1:5,000) were used in densely populated areas.
[12] In total there are about 25,000 km of watercourses in Saxony.
[13] About 2.2% of the total surface area of Saxony.
[14] Geo-coordinates of included households can only be obtained at the research center. Less detailed geo-referenced data can be obtained and used outside the research center.

detailed location information, we make use of this location identifier in our analysis. The Microm identifier localizes households by the geo-coordinates of their living places.[15]

In the third and final step, we match the geo-coordinates of Saxon SOEP households with the combined flood map.[16] Doing so allows us to identify which adult Saxon SOEP respondents lived inside the flooded area, and which respondents lived outside of it, when the August 2002 flood occurred.

As our treatment group, we define those respondents who lived inside the flooded area when the flood occurred in 2002. As our control group, we make use of those respondents identified as living outside the flooded areas.[17] In order to ensure that the control group contains exclusively unaffected SOEP respondents, we include only those individuals living at least 500 meters away from flooded areas when the flood event occurred.[18] While in the growth context it is interesting to study the long-run flood impact, our time perspective is somewhat limited as parts of Saxony experienced another, yet less severe flood, in spring 2006. As this would ultimately threaten our identification strategy, we restrict our post-disaster analysis to the years between 2003 and 2005. However, this perspective nevertheless goes well beyond the short-term growth effect of natural disasters.[19] Finally, we drop those respondents who have been interviewed in 2002 before the flood, but have left the treatment or control region before the flood occurred. This leaves us with a treatment group of 50 persons, and a much larger control group of 1225 persons. Table I shows the summary statistics for all variables in the pre-disaster year (2002), conditional on being a member of the treatment or control group.

[15] For additional information on geographically referenced data and the SOEP, see Hintze and Lakes (2009).
[16] The flood map and the geo-coordinates of Saxon SOEP respondents were matched using the open source software Quantum GIS Dufour.
[17] In our study, being unaffected implies that these individuals should not have suffered directly from the flood catastrophe and therefore did not receive any financial disaster aid by private insurance companies or the state.
[18] Respondents living outside the flooded areas but closer than 500 meters to such an area were excluded from the analysis.
[19] Many empirical studies on the growth effects of natural disasters solely focus on the growth effects in the subsequent year.

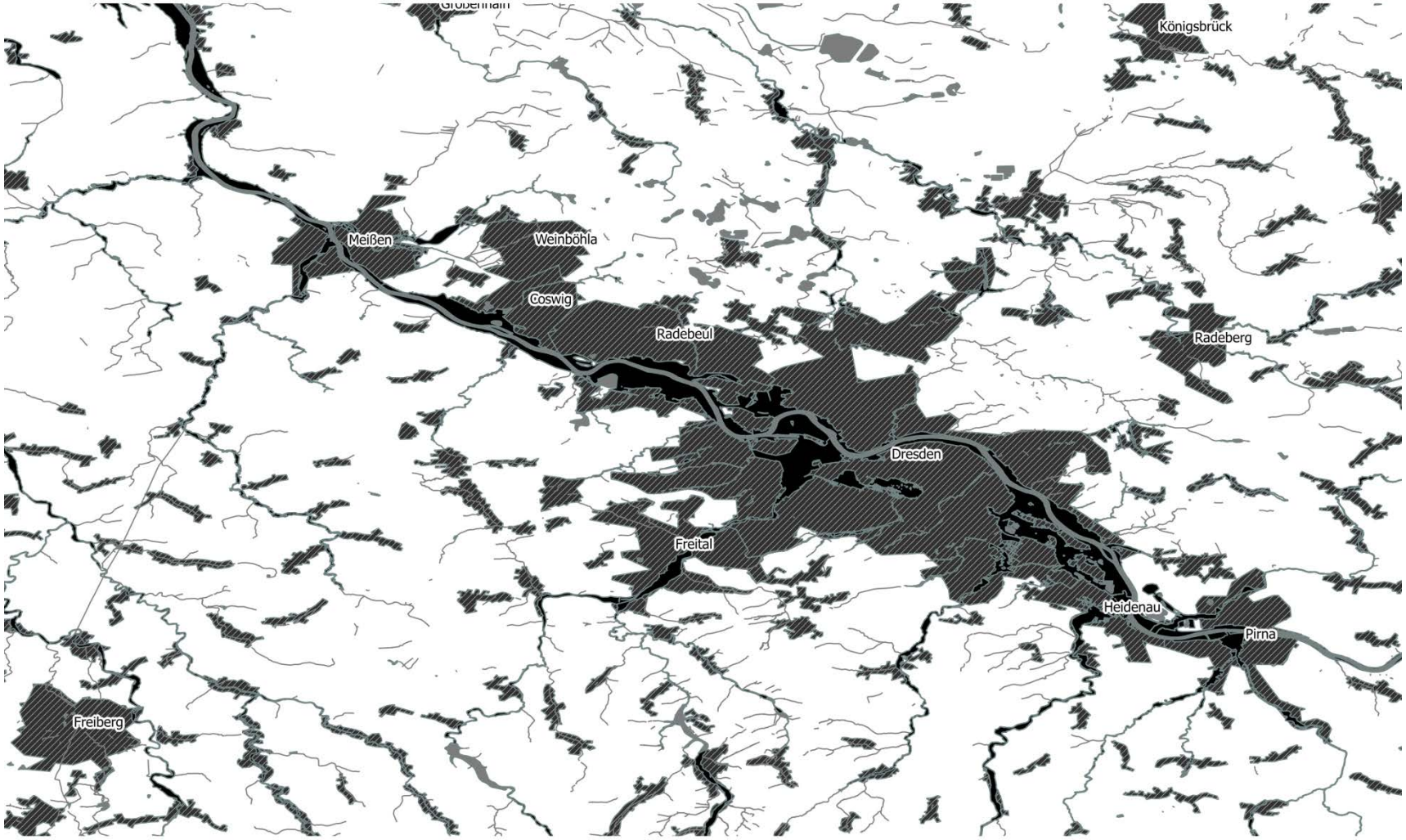
Königsbrück
Meißen
Weinböhla
Coswig
Radebeul
Radeberg
Dresden
Freital
Heidenau
Pirna
Freiberg

Table I: Summary statistics for treatment and control group (Person-Level)

Year 2002	Treatment Group					Control Group				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**	**N**
Saving Volume (S)	118.97	249.13	0	1450.90	50	130.95	239.35	0	3088.835	1180
Binary Saving (S_E) (Yes = 1)	0.66	0.48	0	1	50	0.66	0.47	0	1	1180
Intensive Saving (S_I)	180.26	289.21	11.73	1450.90	33	198.62	271.06	2.11	3088.84	778
Saving Rate (SR)	0.07	0.11	0	0.56	50	0.08	0.11	0	0.95	1178
Controls:										
Sex (Male = 1)	0.47	0.50	0	1	50	0.49	0.50	0	1	1225
Age	44.26	16.07	19	77	50	47.45	16.66	18	91	1225
Homeowner (Yes = 1)	0.59	0.50	0	1	50	0.43	0.50	0	1	1225
Primary Education (Yes = 1)	0.14	0.35	0	1	49	0.11	0.32	0	1	1190
Secondary Education (Yes = 1)	0.59	0.50	0	1	49	0.57	0.50	0	1	1190
Tertiary Education (Yes = 1)	0.27	0.45	0	1	49	0.32	0.47	0	1	1190
Employed (Yes = 1)	0.66	0.48	0	1	50	0.57	0.50	0	1	1225
Unemployed (Yes = 1)	0.10	0.30	0	1	50	0.09	0.28	0	1	1225
Non-working (Yes = 1)	0.24	0.43	0	1	50	0.34	0.48	0	1	1225
Single (Yes = 1)	0.26	0.44	0	1	50	0.24	0.43	0	1	1225
Married (Yes = 1)	0.65	0.48	0	1	50	0.62	0.49	0	1	1225
Other (Yes = 1)	0.10	0.30	0	1	50	0.14	0.35	0	1	1225
No child (Yes = 1)	0.57	0.50	0	1	50	0.68	0.47	0	1	1225
1 child (Yes = 1)	0.28	0.45	0	1	50	0.20	0.40	0	1	1225
2 children (Yes = 1)	0.04	0.20	0	1	50	0.09	0.29	0	1	1225
3+ children (Yes = 1)	0.04	0.20	0	1	50	0.09	0.29	0	1	1225
Living in Rural Area (Yes = 1)	0	0	0	0	50	0.21	0.41	0	1	1225

Summary statistics for the group identified as located inside the flooded region (treated group) and the control group (located at least 500m away from the flooded region but in Saxony). The allocation to each group is based on geo-referenced data. Due to missing answers observations can differ across variables. The statistics are based on SOEP answers in 2002 before the flood occurred in August. A detailed description of listed variables can be found in table AI in the appendix.

3.4 Estimation Strategy

The aim of our empirical analysis is to study whether and how individuals, who lived in the flooded area when the catastrophic flood occurred, adjusted their subsequent saving behavior. In order to study the causal effect of the flood on saving behavior, we apply a difference-in-differences (DD) approach as described below. We hereby follow the basic framework outlined by Angrist and Pischke (2009).

In our setting, we have two regions (1, 2); region 2 was hit by the flood in August 2002. Moreover, we have two periods (before August 2002, after August 2002) for which we can observe individual saving behavior.[20] Given this situation, we have two potential outcomes. S_{1irt} is the saving of individual *i* in region *r* (1, 2) at time *t* (before August 2002, post 2002) if a flood happened, and S_{0irt} is the saving of individual *i* in region *r* at time *t* if no flood happened. However, in reality, we only observe one or the other event. For example, we can see S_{1irt} in region 2 in 2003 but we cannot observe the counterfactual S_{0irt} in region 2 in 2003, since region 2 was affected by the flood in August 2002. The DD setup is based on an additive structure for potential outcomes in the no-treatment scenario:

$$E[S_{0irt}|\, r, t] = \gamma_r + \lambda_t.$$

We therefore assume that saving without a flood is determined by the sum of a time-invariant regional fixed effect (γ_r) and a time effect (λ_t) that is common across regions. Let D_{rt} be a dummy variable for flooded regions and periods. Assuming that $E[S_{1irt} - S_{0irt}|r, t]$ is the constant δ, the observed saving S_{irt} can be written as:

$$S_{irt} = \gamma_r + \lambda_t + \delta D_{rt} + \varepsilon_{irt}, \quad (1)$$

where $E(\varepsilon_{irt}|r, t) = 0$. The expected differences for the two regions are thus:

$$E[S_{irt}|\, r = 1, t = post\ \ 02] - E[S_{irt}|r = 1, t = prior\ Aug\ 02] = \lambda_{post\ \ 02} - \lambda_{prior\ Aug\ 02}$$

[20] De facto we have more than one post-treatment period. For simplicity, we explain the DD approach with two periods only.

and

$$E[S_{irt}|\, r = 2, t = post\ \ 02] - E[S_{irt}|r = 2, t = prior\ Aug\ 02] = \ \lambda_{post\ \ 02} - \lambda_{prior\ Aug\ 02} + \ \delta.$$

The difference between the two expected differences, the difference-in-differences estimator, is thus δ. One way to estimate equations like (1) with additional individual level covariates, $X`_{rit}$, is:

$$S_{rit} = \alpha + \ \gamma treat_r + \ \lambda year_t + \ \delta(treat_r \times year_t) + \beta X`_{rit} + \epsilon_{rit}, \quad (2)$$

where *year* is a dummy variable that switched to 1 in the years after the flood event happened. The dummy *treat* takes the value 1 for region 2 (where the flood occurred in August 2002) and 0 otherwise.

When studying saving behavior, we start out with an analysis of the overall saving volume *S*. As our saving measure cannot be negative, we use the tobit approach in the first step of our analysis. We then turn to separate analyses of the two dimensions of the savings decision: the decision to save at the extensive and intensive margin. As the decision to save or not to save is a binary one, we employ probit regressions for the analysis of the extensive margin of the saving decision (S_E). The decision to save at the intensive margin (S_I) is analyzed based on a log-linear model using standard OLS techniques.

We conduct all our empirical analyses with our sample of SOEP respondents that were attributed to either the treatment or the control group. As we analyze the effect of the flood on saving behavior in three post-disaster years, we report three different estimates (2002/03, 2002/04 and 2002/05). In order to study the stability of the derived results and to further investigate potential factors driving our results, we conduct a number of additional estimations in Sections Five and Six. As it is easier to understand these estimates after learning about the main estimation results in Section Four, we explain those approaches in later sections.

4. Empirical Analysis of Individual Saving Behavior

Our empirical analysis of the flood's impact on saving behavior covers three dimensions: the effect on overall saving S, the effect on the extensive margin S_E, and the effect of the intensive

margin of the saving decision S_I. Thus, we estimate the difference-in-differences regression outlined in Equation (2) using three different dependent variables. As outlined earlier, we make use of different estimation techniques to adequately take the different characteristics of the referring dependent variables into account. In Table 2 we report the estimation results.[21] To ease interpretation, we only report the results for the dummy variables for year and treatment, as well as the interaction between these two dummy variables which captures the treatment effect.[22]

The upper part of Table 2 reports the results of tobit models where we estimate the flood's impact on the latent variable *S.*[23] We report the effect on the uncensored latent variable. Thus, the estimated coefficients can be interpreted as the predicted change in desired saving levels. The estimates suggest that the flood depressed desired saving in all three years succeeding the disaster. However, in 2003 (i.e., the first year after the flooding), the effect is not significant. In 2004 and 2005, the effect becomes significant and also increases in magnitude. We also report the conditional marginal effect on factual saving, which turns out to 59 Euro in 2004 (25 percent) and 69 Euro in 2005 (21 percent).[24] This suggests that the flood had a very strong and lasting effect on individual saving behavior.

The center part of Table 2 shows the results of the probit models that analyze the decision to save at the extensive margin. Experiencing the flood had a negative impact on the decision to save in all post-disaster years analyzed. As for the overall saving decision, the effect of the flood is significant in the years 2004 and 2005. In order to deliver a meaningful interpretation of the estimated coefficients, we compute marginal effects for an individual with median characteristics (i.e., the year and the interaction term were set to 0).[25] For 2004, we find the median individual, impacted by the flood, had 30.5 percentage points lower probability of saving any money, as compared to 2002. Even in 2005 (i.e., three years after the disaster), flood-affected individuals

[21] The number of observations across specifications varies slightly due to missing values of explanatory variables and the choice of the dependent variable.
[22] Full estimation results are provided in the appendix.
[23] Our dependent variable is the logarithm of total household saving S. In cases of households with zero saving, S was manually set to one and hence the logarithm of S was set to zero.
[24] We compute the effect of a switch in the binary interaction term on the latent variable by: 100[exp(coefficient)-1].
[25] Results are also similar when a linear probability model is used. Estimation results are available from the authors on request.

are 23,9 percentage points less likely to save. These findings are in line with the results from our tobit model and suggest a rather strong behavioral reaction to the flood.

Finally, the estimates of the linear model, as reported in the bottom part of Table 2, show the flood's impact at the intensive margin of the saving decision. Note that for the analysis of S_I, only those respondents that save a positive amount before the flood and in the respective post-flood year are included in the analyses. We find no systematic effect on saving, here; however, the number of observations is also very small in this specification because several respondents reduced their savings to zero in 2004 and 2005, as our estimates at the extensive margin have shown.

To sum up, the results of our estimates show that the flood significantly reduced the savings of affected individuals. While we detected no response to the flood at the intensive margin of the saving decision, the effect is significant at the extensive margin of the saving decision two and three years after the disaster.

Table II: Individual Saving Behavior

Model	Variable	2002/03	2002/04	2000/05
Tobit	Dept. Var.: *S*	(I)	(II)	(III)
	year	-8.108	-11.637	0.404
		(0.433)	(0.288)	(0.979)
	treat	-23.774	-16.321	-7.607
		(0.658)	(0.759)	(0.904)
	year x treat	-71.623	-175.168**	-178.232***
		(0.232)	(0.015)	(0.005)
	ME [E(S|S>0)]	-26.917	-59.011**	-69.631***
	Change[1] (in percent)	-10.58	-25.41	-21.40
	Log pseudolikelihood	-10599.234	-9888.180	-9818.446
	Observations	2188	2068	1974
	Left censored Obs.	764	722	683
Probit	Dept. Var.: S_E			
	year	-0.068	-0.072	-0.034
		(0.224)	(0.210)	(0.604)
	treated	-0.012	0.018	0.032
		(0.965)	(0.950)	(0.913)
	year x treated	-0.163	-0.789**	-0.628**
		(0.593)	(0.026)	(0.021)
	ME	-0.058	-0.305**	-0.239**
	Change[2] (in ppt.)	-5.845	-30.535	-23.91
	Log pseudolikelihood	-1285.720	-1218.389	-1155.581
	Observations	2188	2068	1974
OLS	Dept. Var.: S_I			
	year	-13.543	5.776	4.700
		(0.494)	(0.788)	(0.877)
	treated	-110.168	-75.464	-95.487
		(0.174)	(0.523)	(0.368)
	year x treated	-108.249	-133.760	-87.587
		(0.133)	(0.333)	(0.300)
	Adjusted R^2	0.122	0.128	0.123
	Observations	1276	1196	1096

Note, ME stands for marginal effect. ME are computed for a person with characteristics according to the median of all treated individuals in the respective regression sample. Observations can vary between regressions as regression samples are only balanced for the specific year-to-year combination analyzed. All regressions include the control variables depicted in table 1. The interaction terms capture the change in the differences on the outcome between before and after the flood (i.e. the effect of the flood).[1] Refers to the percentage change in saving volume due to the flood to average saving volume of a treated individual in 2002.[2] Refers to the change in the likelihood to save any amount of money due to the flood. The variable S is censored at 0. P-values are reported in parenthesis and standard errors are clustered on the household level. Significance levels:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5. Why Do Affected Individuals Reduce their Savings?

In the previous section, we presented empirical results indicating that the flood in Saxony of August 2002 had an economically important and statistically significant negative effect on saving behavior on those individuals who decided to stay in the disaster-affected area. As stated in the introduction, there are several potential explanations for this finding. In this section, we try to identify which of these explanations is the most likely driving force behind our results.

One possible explanation could be that flood-affected individuals updated their life expectancy after the disaster and consequently changed their time preferences (see, e.g., Callen 2011, Cassar et al. 2011). The observed reduction in savings would imply that affected individuals expect to die earlier. Such a shift in time preferences in the context of the Elbe flooding is unlikely. Germany is a highly developed country with relatively high protective measures (e.g., strict building codes) that should prevent high death tolls in face of natural disasters. Indeed, while more than 330.000 Germans were affected by the 2002 Elbe flood, the death toll was considerably small and amounted to 27 people (CRED). We therefore consider it very unlikely that an update of life expectation is the driving force behind the decision to decrease saving.

A second explanation might be that decreased saving is the consequence of increased expenditures. Individuals severely affected by the flood might have required all of their available income to cope with the consequences of the disaster. However, one might have serious doubts about this explanation. Significant financial aid flows were allotted to affected individuals in the aftermath of the flood event. Affected households received governmental help, payments from charity organizations, or insurance payments shortly after the flood. In addition, aid in kind and neighborhood support were also substantial. For Germany as a whole, more financial aid was available than was needed to deal with the estimated damages of the flood (Mechler and Weichselgartner, 2003). While governmental programs could rely on a national fund of about EUR 7.1 billion, insurance payments and charity payouts for households in Saxony alone amounted to EUR 240 and 362 million, respectively. Governmental aid programs can be divided into two

programs: emergency relief and reconstruction relief.[26] As the name "emergency relief" implies, most of these payments were quickly allotted. In Saxony, nearly all requested emergency relief funds were paid out to affected households by the end of January 2003. Reconstruction relief, aimed at the long term support of affected homeowners, was paid out over the whole period of the reconstruction process. Reconstruction expenses of up to 80% were compensated by the program. By mid-2003, nearly all approved disaster relief was paid out (Leitstelle Wiederaufbau 2003a, b). In light of these facts, it is somewhat doubtful that post-disaster expenses forced the referring individuals to reduce their savings. Moreover, the time-pattern we find in our estimation results does not support the enforced saving argument. A large share of disaster-related expenses likely occurred soon after the disaster. If in fact disaster-related expenses would have enforced decreased savings, we should observe the savings effect to occur quickly after the flood event. However, none of our savings measures decreased significantly before 2004.

A third possible explanation is that the flood could have induced the observed reduction in savings through its impact on the local labor market by reducing individual income (Vigdor 2007, Groen and Polivka 2010, Deryugina et al. 2014a). A reduction in individual income would lead to less disposable income and thus fewer savings. However, the flood's short-term impact on the economy in Saxony was rather moderate (see, e.g., Hoffmann et al. 2004, Müller and Thieken 2005, Berlemann and Vogt 2008). Moreover, the duration of the estimated effect on individual saving behavior makes it unlikely that the reduction is caused through reduced income alone. Household income might have temporarily declined but this effect would not have persistent over a period of three years. For instance, Müller and Thieken (2005) report that businesses interrupted production for two to four days after the flood.

In order to formally check whether our results are primarily driven by income effects, we compute an individual savings rates, *SR*,[27] and run a number of additional regressions. Again we estimate

[26] Emergency relief included three subprograms. The first program aimed to support individuals and was financed by the federal state. This program allotted each person affected by the flood EUR 500, up to EUR 2000 per household. Recipients had to provide a written statement that the money would be used for replacements. The second program was similar to the first but was managed by the national government. The third program supported the emergency reconstruction of dwellings and was administered by the federal state. Owners of dwellings received up to EUR 5,000 for drainage, repairs, and maintenance, if damages were above EUR 10,000.

[27] The individual savings rate is calculated by dividing individual saving S by individual income.

regressions that follow equation (2). However, we now use the savings rate as our dependent variable. The results of the tobit regressions (Table III) are consistent with the earlier presented results reported in Table II. As before, we report the conditional marginal effects on the factual saving rate. While we do not find any significant effect in the first year after the disaster, the flood induced a significant drop in the saving rate in 2004 and 2005. Again, we calculate the percentage change in the saving rate in order to quantify the magnitude. In 2004, the flood exerted a reduction in the factual saving rate of slightly more and 2005 a reduction of slightly less than 2 percentage points. Given these results and our estimates from the tobit model on total saving, we conclude that the reduction in savings were not primarily driven by a decline in income.

Table III: Estimation Results Individual Saving Rate

Model	**Variable**	**2002/03**	**2002/04**	**2002/05**
Tobit	Dept. Var.: *SR*	(I)	(II)	(III)
	year	-0.006	-0.006	-0.006
		(0.319)	(0.272)	(0.354)
	treat	-0.015	-0.012	-0.007
		(0.583)	(0.656)	(0.813)
	year x treat	-0.017	-0.098**	-0.080***
		(0.646)	(0.010)	(0.003)
	ME [SR|SR>0]	-0.007	-0.035**	-0.031***
		(0.454)	(0.015)	(0.007)
	Change[1] (in ppt.)	-0.71	-3.49	-3.09
	Log pseudolikelihood	214.722	270.495	199.660
	Observations	2180	2064	1972
	Left censored	764	720	682

Note, ME stands for Marginal effect. MEs are computed for a person with characteristics according to the median of all treated individuals in the respective regression sample. Observations can vary between regressions as regression samples are only balanced for the specific year-to-year combination analyzed. All regressions include the control variables depicted in table 1. The interaction terms capture the change in the differences on the outcome between before and after the flood (i.e. the effect of the flood). [1] Refers to the change in the saving rate measured in percentage points. The variable SR is computed dividing the individualized monthly amount saved by individual monthly gross income and is censored at 0. P-values are reported in parenthesis and standard errors are clustered on the household level. Significance levels:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Finally, the observed saving pattern could stem from a change in precautionary savings. As outlined earlier, precautionary savings should be reduced whenever the perceived probability of a disaster event and/or a disaster loss decreases. It seems counterintuitive that the occurrence of a disaster should decrease the perceived probability of disasters occurring in the future, as one might expect the opposite to happen instead (see, e.g., Eckel et al. 2009, Cameron and Shah

2013). However, the reduction of precautionary savings might stem from decreased perceived disaster loss. At first glance, again there is little reason to believe that perceived disaster loss decreases as a consequence of the occurrence of a disaster. However, it is well possible that perceived loss is decreased by unexpected financial compensation in the aftermath of a disaster. Given that precautionary savings are intended as insurance against unexpected expenditures (Lusardi 1998), receipt of disaster relief can induce disaster-affected individuals to reduce their savings.[28] In particular, unprecedentedly high compensation rates might induce a reduction in precautionary savings through moral hazard effects. This phenomenon, also known as the Samaritan's Dilemma (Buchanan 1975, Coate 1995) or the Charity Hazard (Raschky and Weck-Hannemann 2007, Dobes et al. 2014), is theoretically convincing, yet, little empirical evidence exists so far.[29] As discussed earlier, the flood victims of the August 2002 event indeed received an immense amount of financial aid (i.e., in addition to the in-kind aid and neighborhood support already mentioned).[30] Compared to disaster aid in other developed countries, compensation was exceptionally high. Linnerooth-Bayer et al. (2001) reported that compensation rates after disasters in several developed countries were around 40% of occurred losses, whereas the Elbe flooding compensation rates provided almost total compensation.[31] Although we have little information on pre-event expectations on disaster compensation, one might nevertheless suspect that the extraordinary disaster aid of the Elbe flood was at least somewhat unexpected. While the generous disaster aid surely helped to quickly overcome the direct consequences of the flood disaster, it is also highly possible that the enormous level of aid indeed caused a moral hazard effect that led to a reduction in self-insurance via precautionary saving. The explanation of decreased saving by the existence of a Samaritan`s Dilemma is further supported by the

[28] In a similar vein, Raschky and Weck-Hannemann (2007) argue that individuals anticipate governmental and private aid in the case of natural disasters and therefore often refrain from purchasing private disaster insurance. For a more detailed discussion, see Antwi-Boasiako (2014).

[29] There is a small amount of empirical literature on the existence of the Samaritan's Dilemma in natural hazard insurance. While the studies by Kunreuther et al. (1978) and Browne and Hoyt (2000) failed to find that government aid crowded out purchasing of private disaster insurance, the studies by van Asseldonk et al. (2002), Botzen et al. (2009), Brunette et al. (2013), Kousky et al. (2013), and Deryugina and Kirwan (2014b) report evidence that supports this argument.

[30] In their analysis of the political consequences of the provided aid in the aftermath of the Elbe flood of 2002, Bechtel and Hainmueller (2011) implicitly assume high compensation rates, which is in line with our line of argument.

[31] In line with this finding, Horwich (2000) reports that the governments of disaster-prone Japan traditionally provide only minimal disaster compensation in order to prevent negative incentive effects.

observed time-pattern in our estimation results. The strong reaction in saving behavior happened in 2004 and 2005, and hence after most financial aid was already been paid out.

6. Placebo and Robustness Tests

In order to study the appropriateness of our identification strategy and the robustness of our estimation results, we present and discuss several additional estimation results in this section.

First and most important, we study whether the assumption of parallel trends in the treatment and control group holds true in the absence of the treatment. As the inferences in the difference-in-differences approach are based on this assumption, we shed some light on this issue by conducting a falsification test. This strategy estimates placebo difference-in-differences regressions that use the same basic specification that was explained in Section Three and employed in Section Four; the only difference is that we assume the flood occurred at some arbitrary point in time before the actual occurrence in August 2002. Whenever the identified differences between the treatment and the control group indeed result from the treatment, we should find that the interaction effect between the treatment and year dummy variables is insignificant in the placebo treatment.

For our placebo treatment, we assume that the flood had already occurred in August 2000 and thus two years before it actually took place.[32] All respondents questioned before August 2000 comprise the pre-treatment sample, and all respondents questioned in 2001 and before August 2002 comprise the post-treatment observations. We included only respondents which took part in the SOEP in between 2000 and 2002. In order to construct the control and the treatment group of the placebo treatment, we use the same procedure as described in Section 3.3.

[32] The geographic data that was used to divide the SOEP participants into the treatment and the control group was unavailable before 2000. We therefore cannot conduct placebo treatments for earlier points in time.

Table IV: Placebo Estimation Results Individual Saving Behavior

Model	Variable	2000/01	2000/02
Tobit	Dept. Var.: *S*	(I)	(II)
	year	-0.393	-15.477
		(0.959)	(0.107)
	treat	-50.814	-43.741
		(0.116)	(0.166)
	year x treat	-9.201	24.455
		(0.782)	(0.376)
	ME [E(S|S>0)]	-3.638	25.125
		(0.784)	(0.240)
	Change[1] (in percent)	-2.05	5.932
	Log likelihood	-10653.729	-10009.988
	Observations	2208	2062
	left censored	703	670
Probit	Dept. Var.: S_E		
	year	-0.014	-0.117*
		(0.815)	(0.076)
	treat	0.080	0.129
		(0.770)	(0.639)
	year x treat	-0.225	-0.034
		(0.301)	(0.862)
	ME	-0.066	-0.060
		(0.319)	(0.911)
	Change[2] (in ppt.)	-6.581	-0.599
	Log pseudolikelihood	-1230.240	-1192.633
	Observations	2208	2062
OLS	Dept. Var.: S_I		
	year	12.878*	-2.250
		(0.059)	(0.826)
	treat	-55.790*	-79.411**
		(0.075)	(0.023)
	year x treat	10.425	30.761
		(0.758)	(0.256)
	R^2	0.171	0.122
	Observations	1382	1242

August 2000 has been chosen as date for the hypothetical flood. Note, ME stands for marginal effect. ME are computed for a person with characteristics according to the median of all treated individuals in the respective regression sample. Observations can vary between regressions as regression samples are only balanced for the specific year-to-year combination analyzed. All regressions include the control variables depicted in table 1. The interaction terms capture the change in the differences on the outcome between before and after the hypothetical flood (i.e. the effect of the flood).[1] Refers to the percentage change in saving volume due to the flood to average saving volume of a treated individual in 2000.[2] Refers to the change in the likelihood to save any amount of money due to the flood. The variable S is censored at 0. P-values are reported in parenthesis and standard errors are clustered on the household level. Significance levels:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table V: Placebo Estimation Results Individual Saving Rate

Model	Variable	2000/01	2000/02
Tobit	Dept. Var.: *SR*	(I)	(II)
	year	0.003	-0.013**
		(0.618)	(0.022)
	treated	-0.037*	-0.034*
		(0.050)	(0.064)
	year x treated	-0.006	0.024
		(0.800)	(0.180)
	ME [E(SR|SR>0)]	-0.003	0.011
		(0.784)	(0.170)
	Change (in ppt.)	-0.258	1.136
	Log-Likelihood	404.673	351.105
	Observations	2204	2058
	Left censored	703	670

August 2000 has been chosen as date for the hypothetical flood. Note, ME stands for marginal effect. MEs are computed for a person with characteristics according to the median of all treated individuals in the respective regression sample. Observations can vary between regressions as regression samples are only balanced for the specific year-to-year combination analyzed. All regressions include the control variables depicted in table 1. The interaction terms capture the change in the differences on the outcome between before and after the hypothetical flood (i.e. the effect of the flood). [1] Refers to the change in the saving rate measured in percentage points. The variable SR is computed dividing the individualized monthly amount saved by individual monthly gross income and is censored at 0. P-values are reported in parenthesis and standard errors are clustered on the household level. Significance levels:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The estimation results for individual saving are displayed in Table IV. In contrast to the results reported in Section 4, the relevant interaction effect between the year and treatment dummy variables is insignificant for both estimations (i.e., the difference between 2000 and 2001 and the difference between 2000 and 2002). Thus, we find no evidence for differing trends between the treatment and the control group in our placebo treatment. In Table V, we show the corresponding estimation results for individual saving rates. Again, we identify no difference in the trends of the treatment and control group.

Throughout the previous empirical analyses of the extensive decision to save, we defined the referring saving variable as:

$$S_E = \begin{cases} 1|S > 0 \\ 0|S = 0 \end{cases}$$

Thus, even individuals with very small but positive reported savings were considered savers. However, one might argue that in the context of disasters, a very low saving volume of only a few Euros should not be considered as precautionary savings. As a second stability test, we defined savers as individuals who declared that they saved more than 50 € a month, i.e.:

$$S'_E = \begin{cases} 1 | S > 50€ \\ 0 | S \leq 50€ \end{cases}$$

Table VI presents the corresponding estimates at the extensive margin. The results remain qualitatively unaffected, while the calculated marginal effects slightly increase. Moreover, the results are now significant on the 99% confidence level.

Table VI: Stability of Estimations Results at the Extensive Margin

Model	**Variable**	**2002/03**	**2002/04**	**2002/05**
Probit	Dept. Var.: S'_E	(I)	(II)	(III)
	year	0.029	-0.013	0.009
		(0.545)	(0.794)	(0.874)
	treated	0.019	-0.022	0.031
		(0.940)	(0.931)	(0.903)
	year x treated	-0.270	-1.054***	-0.735***
		(0.389)	(0.001)	(0.001)
	ME	-0.107	-0.360***	-0.286***
		(0.387)	(0.001)	(0.001)
	Change[1] (in ppt.)	-10.742	-35.975	-28.605
	Log pseudolikelihood	-1279.031	-1221.087	-1185.816
	Observations	2188	2068	1974

Marginal effects are computed for a person with characteristics according to the median of all treated individuals in the respective regression sample. Observations can vary between regressions as regression samples are only balanced for the specific year-to-year combination analyzed. All regressions include the control variables depicted in table 1. The interaction terms capture the change in the differences on the outcome between before and after the flood (i.e. the effect of the flood).[1] Refers to the change in the likelihood to save any amount of money due to the flood. The variable S'_E is 0 for all persons saving EUR 50 or less. P-values are reported in parenthesis and standard errors are clustered on the household level. Significance levels:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Finally, we study whether our estimation results still hold true when we only look at household heads instead of individual household members. In other words, instead of including all household members we only focus on the household heads without imputing any intra-household allocation of household savings. Doing so generally decreases the number of observations but also reduces measurement error in our dependent variable. Due to the small number of

observations, we decided to pool all observations from 2002-2005 and include year dummies, our treatment dummy and year dummies interacted with our treatment dummy for all years except for our baseline year (2002). The resulting estimation results are displayed in table VII.

Table VII: Household Saving Behavior

Model:	**Tobit**	**Probit**	**OLS**	**Tobit**
Dependent Var.:	**(S)**	**(S_E)**	**(S_I)**	**(SR)**
year3 (2003 = 1)	-3.241	-0.036	9.183	-0.003
	(0.864)	(0.527)	(0.686)	(0.615)
year4 (2004 = 1)	-11.473	-0.046	22.805	-0.005
	(0.570)	(0.435)	(0.330)	(0.462)
year5 (2005 = 1)	-12.503	-0.068	4.166	-0.010
	(0.616)	(0.315)	(0.868)	(0.226)
treated (yes = 1)	-36.209	0.012	100.166	-0.011
	(0.757)	(0.968)	(0.643)	(0.802)
year3 x treated	-134.242	-0.125	-341.152*	-0.036
	(0.188)	(0.689)	(0.094)	(0.406)
Marginal effect	-55.4751	-0.047	-	-0.015
	(0.217)	(0.687)		(0.426)
Change	-12.71%	-4.71 ppt.	-	-1.54 ppt.
year4 x treated	-341.631***	-0.828**	-308.233	-0.126***
	(0.006)	(0.023)	(0.238)	(0.003)
Marginal effect	-122.858**	-0.321**	-	-0.046**
	(0.013)	(0.015)		(0.012)
Change	-28.15%	-32.10 ppt.	-	-4.57 ppt.
year5 x treated	-198.432**	-0.506*	-118.224	-0.072**
	(0.025)	(0.095)	(0.399)	(0.026)
Marginal effect	-77.704**	-0.198*	-	-0.028*
	(0.046)	(0.082)		(0.060)
Change	-17.81%	-19.83 ppt.	-	-2.81 ppt.
Log pseudolikelihood	-10478.447	-1174.316	NA	-5.407
Observations	2024	2024	948	1976
Left censored	702	NA	NA	693
Adjusted R^2	NA	NA	0.147	NA

Reference year for all year dummies is 2002. Personal characteristics refer to the head of the household. Household heads are classified as such by the SOEP. Marginal effects are computed for a household head with characteristics according to the median of all treated household heads in the respective regression sample. The marginal effect for the tobit model is on the expected saving volume conditioned on saving any amount of money (E[S|S>0]). The interaction terms capture the change in the differences on the outcome between before and after the flood (i.e. the effect of the flood). The change in case of the tobit model is the percentage change in saving volume due to the flood to average saving volume of a treated individual in 2002. The change in percentage points in case of the probit model is the change in the likelihood to save any amount of money due to the flood. The change in case of the saving rate is the change in the saving rate due to the flood expressed in percentage points. The variables S and SR are censored at 0. SR is computed dividing monthly household net saving by monthly household net income. P-values are reported in parenthesis and standard errors are clustered on household level. Significance levels:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The estimates for total savings and for the extensive decision to save remain qualitatively unchanged. The estimation results for the decision to save at the intensive margin are also similar; however, the effect for the period between 2002 and 2003 is now significant at the 10% level. The pattern of the estimates for the individual saving rate is very similar to the one in our benchmark regression as reported in table II. . The results differ from the earlier reported results only in so far as the effect in 2004 is larger in size. To sum up, the estimates at the level of household heads demonstrate that our benchmark results are not biased by the construction of our individual saving measure and deliver strong support that the flood has affected saving behavior in the described way.

7. Summary and Conclusions

In this paper, we presented empirical evidence illuminating the ways in which severe natural disasters might influence individual saving behavior. Using the example of the August 2002 flood catastrophe in Europe, we showed that individual saving decisions were strongly depressed by the flood event. While we cannot provide a formal test for this line of reasoning, the available empirical evidence supports the hypothesis that the reduction of savings was the consequence of the generous financial support that German policymakers provided to flood victims in the aftermath of the catastrophe. While this policy helped to quickly overcome the direct consequences of the disaster quite, it likely caused a Samaritan's Dilemma by decreasing the incentive for precautionary saving among the affected individuals. Thus, our findings highlight the tradeoff between short-term disaster relief and long-run moral hazard effects.

Our results must be carefully interpreted, as we derived them from a natural experiment in a highly developed country. Provided our explanation that the presence of a Samaritan's Dilemma is correct, such a dilemma can only occur as a consequence of high compensation rates. Thus, our findings can only be transferred to situations with comparably generous disaster aid.

Our finding that natural disasters can affect individual saving behavior might also help to explain why natural disasters tend to have long-run growth effects. Whenever saving rates permanently decrease as a consequence of a natural disaster, this translates into lower per-capita growth.

However, in order to find out whether natural disasters do indeed have long-run consequences for individual saving behavior, it would be necessary to track individual saving behavior for an even longer period of time than the three year follow-up period of our empirical analysis. While this perspective is longer than the one taken in most of the existing empirical literature, it would be intriguing to study individual saving decisions for additional years. However, due to the fact that Saxony experienced an additional (although much less severe) flood in 2006, we have to refrain from extending our econometric analysis beyond 2005.

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Appendix

Table A1: Description of Variables

Variable	Description
S	Amount saved per month discounted to 2000 prices using the price index provided by the German federal statistical office. As the variable is only reported on the household level, the amount saved is allocated to all members of the household older than 18 using individual gross income relative to the sum of gross individual income[1] of all household members in a given year.
S_E	Binary variable. Extensive margin of the saving decision. One if S is greater than one and zero otherwise.
S_I	Intensive margin of the saving decision. Only observations for which S is greater than zero.
S'_E	Binary variable. One if S is greater than EUR 50 and zero otherwise.
SR	Saving rate. The individual monthly amount saved (S) divided by the individual's gross income.
Sex	Binary variable. One if individual is male and zero if female.
Age	Age of individual.
Homeowner	Binary variable. One if household owns the dwelling they live in and zero otherwise.
Rural	Binary variable. One if household lives in a rural area and otherwise.
Primary Education	Reference category.
Secondary Education	Binary (factor) variable. One if the highest education obtained is secondary and zero otherwise.
Tertiary Education	Binary (factor) variable. One if the highest education obtained is tertiary and zero otherwise.
Single	Reference category.
Married	Binary (factor) variable. One if the person is married, zero otherwise.
Other	Binary (factor) variable. One if the person is divorced, widowed or married but living apart and zero otherwise.
No child	Reverence category.
One Child	Binary (factor) variable. One if one child lives in household and zero otherwise.
Two Children	Binary (factor) variable. One if two children live in household and zero otherwise.
Two + Children	Binary (factor) variable. One if three or more children live in household and zero otherwise.

[1] includes all reported income sources of an individual reported in the person-level survey of the SOEP.

Table A2: Effect on Individual Saving Volume (balanced regressions)

Tobit Regression	(1)	(2)	(3)
Var. / Dep. Var.:	S	S	S
Year	-8.108	-11.637	0.404
	(10.341)	(10.955)	(15.355)
Treated	-23.774	-16.321	-7.607
	(53.620)	(53.078)	(62.799)
Year x Treated	-71.623	-175.168**	-178.232***
	(59.872)	(72.204)	(62.958)
Sex	54.680***	59.920***	69.552***
	(12.400)	(10.588)	(13.810)
Age	2.712***	3.088***	2.392**
	(0.985)	(0.855)	(0.983)
Homeowner	35.780	23.098	23.106
	(22.651)	(19.822)	(24.755)
Primary			
1.Secondary	31.927	28.474	-12.134
	(19.497)	(18.427)	(36.217)
2.Tertiary	168.600***	141.275***	127.179***
	(28.538)	(23.495)	(40.217)
Working			
1.Unemployed	-280.895***	-260.394***	-363.850***
	(33.822)	(29.022)	(46.502)
2.Non-Working	-107.319***	-113.326***	-132.818***
	(21.647)	(20.061)	(24.290)
Single			
1.Married	6.039	5.552	35.565
	(35.851)	(29.222)	(35.481)
2.Other	19.299	-7.971	38.422
	(43.054)	(37.585)	(47.547)
No Child			
1.One Child	-34.553	-25.633	-20.089
	(27.573)	(25.665)	(28.820)
2.Two Children	-141.416***	-95.973**	-90.577
	(44.773)	(38.974)	(56.508)
3.Two + Children	-127.893*	-83.553	-190.916***
	(74.787)	(77.553)	(65.959)
Rural	-56.259**	-25.805	-33.961
	(25.303)	(22.827)	(31.527)
Constant	-101.187***	-108.376***	-82.989*
	(39.023)	(35.444)	(44.887)
Sigma	288.269***	258.998***	342.330***
	(27.238)	(17.740)	(40.681)
Log pseudolikelihood	-10599.234	-9888.180	-9818.446
Observations	2188	2068	1974
Censored	764	722	683

We report coefficients on the latent variable. See footnotes table II. Standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. SE clustered on household level.

Table A3: Effect on Individual Extensive Margin (balanced regression)

Probit Regression	(1)	(2)	(3)
Var. / Dep. Var.:	S_E	S_E	S_E
Year	-0.068	-0.072	-0.034
	(0.056)	(0.058)	(0.066)
Treated	-0.012	0.018	0.032
	(0.286)	(0.289)	(0.295)
Year x Treated	-0.163	-0.789**	-0.628**
	(0.304)	(0.355)	(0.272)
Sex	0.041	0.043	0.046
	(0.042)	(0.045)	(0.045)
Age	0.011**	0.013***	0.012***
	(0.004)	(0.004)	(0.004)
Homeowner	0.034	0.003	-0.057
	(0.105)	(0.104)	(0.101)
Primary			
1.Secondary	0.002	0.013	-0.069
	(0.107)	(0.112)	(0.117)
2.Tertiary	0.316**	0.327**	0.243*
	(0.127)	(0.128)	(0.132)
Working			
1.Unemployed	-1.014***	-0.983***	-1.173***
	(0.115)	(0.113)	(0.120)
2.Non-Working	-0.194**	-0.194**	-0.228**
	(0.095)	(0.092)	(0.091)
Single			
1.Married	0.127	0.046	0.074
	(0.142)	(0.148)	(0.141)
2.Other	-0.136	-0.353**	-0.342**
	(0.164)	(0.173)	(0.162)
No Child			
1.One Child	-0.037	0.028	0.079
	(0.133)	(0.136)	(0.129)
2.Two Children	-0.489***	-0.319*	-0.323*
	(0.189)	(0.188)	(0.180)
3.Two + Children	-0.655**	-0.682**	-0.523**
	(0.290)	(0.271)	(0.248)
Rural	-0.160	0.033	-0.074
	(0.119)	(0.130)	(0.124)
Constant	-0.001	-0.095	0.052
	(0.193)	(0.192)	(0.199)
Log pseudolikelihood	-1285.720	-1218.389	-1155.581
Observations	2188	2068	1974

See footnotes table II. Standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. SE clustered on household level.

Table A4: Effect on Individual Intensive Margin (balanced regression)

Linear Regression	(1)	(2)	(3)
Var. / Dep. Var.:	S_I	S_I	S_I
Year	-13.543	5.776	4.700
	(19.782)	(21.420)	(30.342)
Treated	-110.168	-75.464	-95.487
	(80.817)	(117.896)	(105.987)
Year x Treated	-108.249	-133.760	-87.587
	(71.871)	(137.898)	(84.398)
Sex	-5.358	-0.696	-7.204
	(17.386)	(11.151)	(12.947)
Age	-1.976	-1.658	-3.013
	(1.831)	(1.638)	(2.089)
Homeowner	178.735***	148.158***	176.024***
	(59.852)	(40.140)	(46.960)
Primary			
1.Secondary	84.674**	60.101*	69.931*
	(37.167)	(34.764)	(39.227)
2.Tertiary	293.710***	185.286***	254.676***
	(65.896)	(47.075)	(61.181)
Working			
1.Unemployed	-177.198***	-154.377***	-206.351***
	(59.604)	(50.069)	(63.410)
2.Non-Working	-104.474**	-107.957***	-149.555***
	(41.115)	(37.178)	(45.781)
Single			
1.Married	-3.838	73.798	144.077**
	(66.881)	(50.017)	(67.697)
2.Other	-46.808	24.119	124.527*
	(73.682)	(60.837)	(74.527)
No Child			
1.One Child	-121.692	-86.350	-90.664*
	(74.535)	(54.689)	(54.910)
2.Two Children	-269.129***	-190.542***	-237.705**
	(91.900)	(73.449)	(94.793)
3.Two + Children	-125.298	177.137	-250.787***
	(104.758)	(134.341)	(96.387)
Rural	-99.170*	-76.005*	-84.561*
	(59.401)	(45.328)	(46.803)
Constant	407.723***	344.274***	373.064***
	(84.230)	(76.932)	(80.665)
Adjusted R^2	0.122	0.128	0.123
Observations	1276	1196	1096

See footnotes table II. Standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. SE clustered on household level.

Table A5: Effect on Individual Saving Rate (balanced regression)

Tobit Regression	(1)	(2)	(3)
Var. / Dep. Var.:	SR	SR	SR
Year	-0.006	-0.006	-0.006
	(0.006)	(0.005)	(0.006)
Treated	-0.015	-0.012	-0.007
	(0.027)	(0.027)	(0.028)
Year x Treated	-0.017	-0.098**	-0.080***
	(0.037)	(0.038)	(0.027)
Sex	0.005	0.007	0.009*
	(0.005)	(0.005)	(0.005)
Age	0.002***	0.002***	0.001***
	(0.001)	(0.000)	(0.000)
Homeowner	0.021*	0.018	0.019*
	(0.011)	(0.011)	(0.011)
Primary			
1.Secondary	0.011	0.013	0.005
	(0.013)	(0.012)	(0.013)
2.Tertiary	0.046***	0.042***	0.043***
	(0.014)	(0.013)	(0.015)
Working			
1.Unemployed	-0.110***	-0.102***	-0.135***
	(0.015)	(0.014)	(0.017)
2.Non-Working	0.003	-0.002	-0.004
	(0.011)	(0.011)	(0.011)
Single			
1.Married	-0.007	-0.008	-0.002
	(0.016)	(0.015)	(0.016)
2.Other	-0.014	-0.019	-0.020
	(0.020)	(0.020)	(0.020)
No Child			
1.One Child	-0.013	-0.007	-0.005
	(0.014)	(0.014)	(0.013)
2.Two Children	-0.063***	-0.048**	-0.058***
	(0.020)	(0.019)	(0.020)
3.Two + Children	-0.082**	-0.082***	-0.103***
	(0.034)	(0.031)	(0.026)
Rural	-0.030**	-0.015	-0.021
	(0.012)	(0.012)	(0.013)
Constant	-0.033	-0.039*	-0.021
	(0.021)	(0.020)	(0.022)
Sigma	0.139***	0.132***	0.139***
	(0.007)	(0.007)	(0.007)
Log pseudolikelihood	214.722	270.495	199.660
Observations	2180	2064	1972
Censored	764	720	682

We report coefficients on the latent variable. See footnotes table III. Standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. SE clustered on household level.

Table A6: Placebo Individual Saving Behavior (balanced regression)

Model (Dep. Var.)	Tobit (S)		Probit (S_E)		OLS (S_I)	
	(1)	(2)	(3)	(4)	(5)	(6)
Variable / Years	2000/01	2000/02	2000/01	2000/02	2000/01	2000/02
Year	-0.393 (7.707)	-15.477 (9.609)	-0.014 (0.059)	-0.117*(0.066)	12.878*(6.793)	-2.250 (10.221)
Treated	-50.814 (32.284)	-43.741 (31.581)	0.080 (0.273)	0.129 (0.274)	-55.790*(31.279)	-79.411**(34.711)
Year x Treated	-9.201 (33.313)	24.455 (27.627)	-0.225 (0.217)	-0.034 (0.196)	10.425 (33.858)	30.761 (27.025)
Sex	36.125*** (8.654)	38.011*** (9.554)	-0.002 (0.045)	-0.019 (0.044)	49.201***(8.978)	50.385***(10.471)
Age	4.473*** (0.777)	3.516*** (0.771)	0.018***(0.004)	0.011***(0.004)	4.016***(0.732)	3.305***(0.904)
Homeowner	54.474***(15.630)	45.484*** (17.524)	0.295***(0.109)	0.163 (0.106)	17.404 (14.286)	23.243 (17.284)
Primary						
1.Secondary	50.931***(16.226)	42.419*** (16.419)	0.168 (0.118)	0.134 (0.106)	37.564***(13.353)	40.042***(15.102)
2.Tertiary	137.215***(19.716)	125.127***(22.546)	0.452***(0.136)	0.406*** (0.123)	102.006***(16.471)	103.133***(21.553)
Working						
1.Unemployed	-205.862***(20.797)	-210.379***(24.236)	-0.936***(0.113)	-0.881***(0.122)	-131.681***(13.375)	-141.965***(15.433)
2.Non-Working	-101.660***(16.986)	-98.829***(17.457)	-0.192**(0.096)	-0.235***(0.091)	-117.413***(16.558)	-114.438***(19.900)
Single						
1.Married	-34.516 (24.725)	-20.267 (27.477)	0.075 (0.135)	0.133 (0.128)	-68.123***(23.362)	-50.820 (32.493)
2.Other	-22.632 (32.245)	-14.964 (32.102)	-0.274 (0.167)	-0.159 (0.154)	0.264 (30.905)	12.251 (37.625)
No Child						
1.One Child	-15.276 (22.454)	-14.284 (25.783)	-0.063 (0.147)	-0.097 (0.146)	4.635 (21.324)	0.401 (30.606)
2.Two Children	-34.080 (28.936)	-57.121**(28.792)	-0.371**(0.170)	-0.420**(0.164)	33.692 (27.244)	-2.070 (28.299)
3.Two + Children	17.925 (80.924)	-64.528 (78.042)	-0.550**(0.280)	-0.865***(0.262)	190.123 (147.471)	141.987 (141.382)
Rural	-39.760** (18.835)	-32.729 (20.314)	-0.189 (0.122)	-0.102 (0.125)	-22.362 (18.327)	-34.542*(19.039)
Constant	-158.122***(31.457)	-114.959***(32.602)	-0.404**(0.186)	-0.042 (0.179)	-18.362 (28.068)	12.494 (30.021)
Sigma	205.368***(11.560)	227.751***(20.325)	NA	NA	NA	NA
Log pseudolikelihood	-10653.729	-10009.988	-1230.240	-1192.633	NA	NA
Adjusted. R^2	NA	NA	NA	NA	0.171	0.122
Observations	2208	2062	2208	2062	1382	1242
Censored	703	670	NA	NA	NA	NA

For the Tobit model we report coefficients on the latent variable. See footnotes table IV. Standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. SE clustered on household level.

Table A7: Placebo Test – Individual Saving Rate (balanced regression)

Tobit Regression	(1)	(2)
Var. / Dep. Var.:	SR	SR
Year	0.003	-0.013**
	(0.005)	(0.006)
Treated	-0.037*	-0.034*
	(0.019)	(0.018)
Year x Treated	-0.006	0.024
	(0.022)	(0.018)
Sex	0.002	0.001
	(0.005)	(0.005)
Age	0.003***	0.002***
	(0.001)	(0.001)
Homeowner	0.041***	0.032***
	(0.011)	(0.011)
Primary		
1.Secondary	0.021*	0.020*
	(0.012)	(0.011)
2.Tertiary	0.048***	0.043***
	(0.014)	(0.013)
Working		
1.Unemployed	-0.093***	-0.091***
	(0.014)	(0.014)
2.Non-Working	-0.004	-0.002
	(0.010)	(0.010)
Single		
1.Married	-0.022	-0.014
	(0.017)	(0.016)
2.Other	-0.032	-0.021
	(0.021)	(0.020)
No Child		
1.One Child	-0.014	-0.013
	(0.014)	(0.014)
2.Two Children	-0.028	-0.032*
	(0.019)	(0.018)
3.Two + Children	-0.048*	-0.088***
	(0.028)	(0.027)
Rural	-0.032***	-0.024**
	(0.012)	(0.012)
Constant	-0.074***	-0.041*
	(0.023)	(0.021)
Sigma	0.129***	0.129***
	(0.005)	(0.006)
Log pseudolikelihood	404.673	351.105
Observations	2204	2058
Censored	703	670

We report coefficients on the latent variable. See footnotes table V. Standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. SE clustered on household level.

Table A8: Stability Test – Individual Extensive Margin (balanced regression)

Log-Linear Regression	(1)	(2)	(3)
Var. / Dep. Var.: S_E' [S_E'=1|S > 50€]	S'_E	S'_E	S'_E
Year	0.029	-0.013	0.009
	(0.048)	(0.052)	(0.058)
Treated	0.019	-0.022	0.031
	(0.246)	(0.253)	(0.256)
Year x Treated	-0.270	-1.054***	-0.735***
	(0.314)	(0.330)	(0.229)
Sex	0.153***	0.198***	0.186***
	(0.050)	(0.051)	(0.050)
Age	0.024***	0.026***	0.024***
	(0.004)	(0.004)	(0.004)
Homeowner	0.034	0.021	-0.014
	(0.098)	(0.096)	(0.095)
Primary			
1.Secondary	0.374***	0.269**	0.192
	(0.116)	(0.119)	(0.120)
2.Tertiary	0.813***	0.668***	0.608***
	(0.132)	(0.133)	(0.132)
Working			
1.Unemployed	-1.380***	-1.451***	-1.395***
	(0.142)	(0.131)	(0.138)
2.Non-Working	-0.489***	-0.516***	-0.533***
	(0.102)	(0.094)	(0.097)
Single			
1.Married	0.035	-0.021	-0.053
	(0.138)	(0.143)	(0.137)
2.Other	-0.086	-0.211	-0.248
	(0.168)	(0.173)	(0.160)
No Child			
1.One Child	-0.044	0.099	0.077
	(0.127)	(0.128)	(0.123)
2.Two Children	-0.413**	-0.237	-0.167
	(0.171)	(0.178)	(0.172)
3.Two + Children	-0.767***	-0.472*	-0.641**
	(0.260)	(0.279)	(0.273)
Rural	-0.139	-0.061	-0.106
	(0.111)	(0.116)	(0.119)
Constant	-1.325***	-1.314***	-1.083***
	(0.204)	(0.198)	(0.191)
Log pseudolikelihood	-1279.031	-1221.087	-1185.816
Observations	2188	2068	1974

See footnotes table VI. Standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. SE clustered on household level.

Table A9: Stability Test – Household Saving Behavior (balanced regression)

Model:	Tobit	Probit	OLS	Tobit
Dependent Var.:	(S)	(S_E)	(S_I)	(SR)
year3 (2003 = 1)	-3.241	-0.036	9.183	-0.003
	(18.851)	(0.057)	(22.709)	(0.007)
year4 (2004 = 1)	-11.473	-0.046	22.805	-0.005
	(20.196)	(0.059)	(23.380)	(0.007)
year5 (2005 = 1)	-12.503	-0.068	4.166	-0.010
	(24.936)	(0.067)	(25.025)	(0.008)
treated (yes = 1)	-36.209	0.012	100.166	-0.011
	(116.914)	(0.305)	(215.624)	(0.044)
year3 x treated	-134.242	-0.125	-341.152*	-0.036
	(101.949)	(0.313)	(202.821)	(0.044)
year4 x treated	-341.631***	-0.828**	-308.233	-0.126***
	(124.324)	(0.365)	(260.373)	(0.043)
year5 x treated	-198.432**	-0.506*	-118.224	-0.072**
	(88.267)	(0.303)	(139.815)	(0.032)
Sex	9.780	0.049	-25.491	0.010
	(39.650)	(0.102)	(45.505)	(0.014)
Age	3.065*	0.015***	-0.248	0.002**
	(1.686)	(0.005)	(2.019)	(0.001)
Homeowner	49.995	-0.117	133.903***	0.013
	(40.087)	(0.105)	(44.979)	(0.015)
Primary				
1.Secondary	16.786	0.109	31.231	0.014
	(59.035)	(0.169)	(46.882)	(0.025)
2.Tertiary	247.487***	0.464**	206.972***	0.069***
	(65.150)	(0.180)	(55.948)	(0.026)
Working				
1.Unemployed	-399.251***	-0.929***	-179.338**	-.130***
	(62.864)	(0.138)	(80.789)	(0.024)
2.Non-Working	-123.284***	-0.060	-154.783***	-0.009
	(44.391)	(0.122)	(53.147)	(0.018)
Single				
1.Married	52.308	0.142	3.518	-0.011
	(58.643)	(0.159)	(68.372)	(0.022)
2.Other	-92.691	-0.321*	-52.610	-0.041
	(65.786)	(0.178)	(72.636)	(0.025)
No Child				
1.One Child	-34.773	0.043	-59.778	-0.014
	(52.006)	(0.129)	(61.905)	(0.018)
2.Two Children	-141.202*	-0.227	-141.053	-0.059**
	(81.884)	(0.180)	(105.314)	(0.026)
3.Two + Children	-227.673*	-0.540*	66.069	-.126***
	(135.129)	(0.286)	(102.084)	(0.042)
Rural	-45.102	-0.008	-88.704*	-0.014
	(45.501)	(0.122)	(45.673)	(0.016)
Constant	-47.529 (97.550)	-0.374 (0.270)	387.933***(116.579)	-0.014 (0.040)
Sigma	460.260***(34.794)	NA	NA	0.161***(0.007)
Log pseudolikelihood	-10478.447	-1174.316	-6955.626	-5.407
Observations	2024	2024	948	1976
Censored	702	NA	NA	693

See footnotes table VII. Standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. SE clustered on household level.

Hurricane Risk, Happiness and Life Satisfaction

Some Empirical Evidence on the Indirect Effects of Natural Disasters

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May 13, 2015

As a consequence of climate change, certain types of natural disasters become either more likely or more severe. While disasters might have numerous direct (typically negative) effects, the effect of an increase of natural disaster risk on individual well-being is often neglected. In this paper we study the effects of natural disaster risk on self-reported happiness and life satisfaction at the example of tropical storms. Combining several waves of the World Values Survey and appropriate storm data we find that perceived disaster risk tends to have little systematic effect on self-reported happiness, once we correct for individual characteristics. However, hurricane risk turns out to decrease life satisfaction significantly, especially in comparatively poor countries. We conclude that when individuals evaluate their long-term satisfaction with their life, disaster risk is perceived as threat to individual well-being.

Keywords: Happiness; Life Satisfaction; Well-Being; Natural Disasters

JEL classification: I31,Q54

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1 Introduction

The world has seen many natural disasters over the years. Some of the worst disasters such as the earthquake in Syria of 1202 with a death toll of more than a million are documented in our history books. Others made it even to the classic literature, such as the destruction of Pompeji in consequence of the eruption of the Vesuv volcano in 79 a.D., which became the central topic of Friedrich Schiller's elegy of 1796 "Pompeji and Herkulaneum". The various types of natural disasters occur in almost all countries around the globe, however with differing intensities and in differing frequencies.

Although natural disasters have affected human well-being ever since, for long periods of time the economic effects of natural disasters have been unexplored. Throughout the last decade, research on the economic effects of natural disasters has been intensified as a consequence of the rising interest in the process of global warming. The term "global warming" refers to the phenomenon of increasing average surface temperatures.[1] According to the Intergovernmental Panel on Climate Change (IPCC) global average surface temperature increased in the interval between 1880 and 2012 by approximately 0.9°C. The prevailing opinion among scientists is that human activities contributed considerably to global warming, especially by burning fossil fuel, thereby increasing the concentration of greenhouse gases in the atmosphere (Intergovernmental Panel on Climate Change 2013). Moreover, the process of global warming is expected to continue even under the assumption of massive reductions in future emissions (see e.g. Solomon et al. 2009). The rise of global temperatures is responsible for a broad range of changes, among them a rising sea level (Cazenave and Nerem 2004), species extinctions and the spread of diseases (e.g. Malaria) to more regions. Moreover, global warming likely will affect the frequency and/or the severity of certain types of natural disasters, among them floods (Milly et al. 2002) and hurricanes (Hoyos et al. 2006).[2] Against this backdrop, scientific interest in the effects of natural disasters has increased considerably.

Most of the research on the effects of natural disasters is empirical in nature.[3] The literature on short-term effects of natural disasters can be subdivided into studies concerned with the direct and the indirect effects of natural disasters (Cavallo and Noy 2011). A first strand of the literature is concerned with direct damages of natural disasters, such as damages to fixed assets and capital, raw materials, extractable natural resources, mortality, and morbidity. Major findings of this literature are that the direct

[1] Global warming is related to the more general phenomenon of climate change, which refers to changes in the the sum of all attributes defining climate, among them surface temperatures, but also precipitation patterns, winds and ocean currents.

[2] See also van Aalst (2006) and Thomas (2014) for a discussion of the interdependence between climate change and natural disasters.

[3] For a more detailed discussion of the related literature see Cavallo and Noy (2011).

effects of natural disasters strongly depend on the level of development of the affected countries (e.g. Kahn 2005) and the quality of institutions (e.g. Skidmore and Toya 2007). A second strand of the literature is concerned with the indirect effects of natural disasters. Most of the existing studies focus on income effects, however, other issues such as employment and inflation have also been studied. In the short-run, most empirical studies find negative effects of disasters on income (e.g. Noy 2009, Raddatz 2009, Fomby, Ikeda and Loayza 2013, Felbermayr and Gröschl 2014).[4] While studies with longer time-horizons are recently gaining more interest, they are still relatively rare and yet failed to deliver consistent results (e.g. Skidmore and Toya 2002, Noy and Nualsri 2007, Jaramillo 2009, Hsiang and Jina 2014.)

Only recently, the economic literature has considered that the effects of natural disasters might go well beyond the issue of macroeconomic growth. Natural disasters might affect an individual's well-being through a direct and an indirect channel. Natural disasters might directly affect an individual's health or employment status, individual wealth or income. All these factors have found to be significant determinants of subjective measures of self-reported individual well-being (see, e.g., Frey and Stutzer 2002). Thus, individuals losing their jobs, getting injured, losing wealth or income in the consequence of an occurring natural disaster will likely report lower life satisfaction and/or happiness because their living conditions are directly affected by disasters. However, natural disasters might also affect individual well-being through a more indirect channel. The mere possibility that natural disasters might occur and affect individual living conditions might be an additional source of individual disutility. If this holds true, high disaster risk should go along with low self-reported well-being.

Interestingly enough, the question whether disaster risk has a significant effect on self-reported well-being has rarely been touched upon. Most of the few related papers are concerned with the direct effect of certain disasters and not with disaster risk in a more general sense. A first strand of this literature uses happiness or life satisfaction data to evaluate the true losses from disasters. While parts of this literature are more generally concerned with the effects of environmental quality or climate on well-being (e.g. Welsch 2002, Rehdanz and Maddison 2008, Luechinger 2009, Rehdanz and Maddison 2011), some recent papers are explicitly concerned with (certain types of) natural disasters (Luechinger and Raschky 2009, Carroll, Frijters and Shields 2008, Kountouris and Remoundou 2011 and Rehdanz et al. 2013). A second strand of the literature focuses more directly on the effects of certain natural disasters on subjective well-being (Kimball et al. 2006, Berger 2010, Yamamura 2012).[5]

In this paper we contribute to filling the described gap in the literature by studying

[4] In some cases, the initially negative effects temporarily turn into positive growth effects as a consequence of rebuilding efforts, see e.g. Berlemann and Vogt (2008).

[5] In Section 2 we summarize this literature in more detail.

whether the perceived risk from hurricanes, a specific and highly destructive form of storms which can occur in many regions around the globe, has a systematic effect on individual well-being. Based on three waves of the integrated European/World Values Survey we run a series of pooled ordered logit regressions to study whether the perceived risk of severe tropical storms has a significant impact on happiness and/or life satisfaction. As the integrated European/World Values Survey itself contains no information on perceived hurricane risk, we have to add measures of perceived hurricane risk from different sources to the dataset. Most existing studies of the effects of natural disasters employ frequency or damage data from the EM-DAT database.[6] However, the EM-DAT data is collected from various different sources and thus is likely contaminated with measurement error since the reporting sources differ in their motives, methodologies and quality of reporting disaster damages (Strobl 2012). We therefore refrain from using EM-DAT data, here, and make use of more systematic records of the occurrence and severity of hurricanes, the Best Track Dataset of tropical cyclones jointly provided by the National Oceanic and Atmospheric Administration (NOAA), the Tropical Prediction Center and the Oceanography Center / Joint Typhoon Warning Center.[7] Based on this dataset we calculate both, a frequency and a severity indicator of hurricane risk on an annual basis. We assume that individuals base their risk assessment on hurricanes which occurred in the past. As we have little information on how many years individuals take into account in their assessment of hurricane risk, we allow for a wide range of alternative specifications.

Based on our estimation results we conclude that the contemporaneous dimension of well-being, self-reported happiness, shows little systematic relation to our measures of perceived disaster risk. If at all, happiness reacts to hurricane events which occurred in the very recent past. However, we find strong empirical support for the hypothesis that life satisfaction as the more long-term oriented component of well-being is affected negatively by perceived hurricane risk. We find the effect to be especially pronounced in comparatively poor countries.

The paper is organized as follows: Section 2 delivers an overview on the literature studying the effects of natural disasters on happiness or life-satisfaction. The 3rd section introduces the employed data and delivers some summary statistics. Section 4 outlines the estimation approach and delivers the results for our baseline regressions. Section 5 deals with the effect of hurricane risk on happiness, section 6 delivers the results for life satisfaction. Section 7 extends the analysis for the subgroups of comparatively poor and relatively rich countries. Section 8 summarizes the main results and draws some conclusions.

[6]For more information on the databse see http://www.emdat.be

[7]We provide a more detailed description of the data sources in the data section.

2 Related Literature

The empirical literature related to this paper evolved out of the broad strand of literature on the determinants of happiness and life satisfaction.[8] Although the terms happiness and life satisfaction are often used interchangeably, the two concepts do not coincide. However, both are related and can be thought of as elements of subjective well-being, i.e. "a state of stable, global judgment of life quality and the degree to which people evaluate the overall quality of their lives positively" (Yang 2008, p. 204.). While especially the concept of happiness is quite controversial and not equally defined across all disciplines concerned with happiness, most will agree that happiness is a subjective, positive, and inner psychological state of mind (Tsou and Liou 2001). However, no consensus is yet reached on the issue whether happiness is a measure of emotion, of thought or even both (Crooker and Near 1998). However, according to both interpretations happiness refers to the comparatively short-term and more volatile component of individual well-being. The concept of life satisfaction is much less controversial. Life satisfaction generally refers to the summation of evaluations regarding a person's life as a whole. Most researchers agree that measures of life satisfaction are cognitive (Crooker and Near 1998). Life satisfaction can be thought of as the less volatile long-term component of individual well-being.

Previous research on happiness and life satisfaction has identified a number of significant determinants of subjective well-being.[9] Various individual characteristics have found to play a systematic role in explaining subjective well-being such as age, marriage, the health status and disabilities. The results for other individual factors such as gender, having children and education are less clear-cut.[10] Economic factors such as individual unemployment and income have also often been studied. While unemployment and job dissatisfaction reduce subjective well-being, the effect of income is highly controversial. Easterlin (1974) reported the peculiar finding that income and happiness are positively correlated within the cross-section- but not in the time-dimension, a finding which is often referred to as "Easterlin Paradox" (see also Easterlin 1995). However, this result has often been challenged (see, e.g., Hagerty and Veenhoven 2003, Stevenson and Wolfers 2008).

Empirical studies of the influence of natural disasters on subjective well-being have been conducted only recently. As outlined earlier, this yet comparatively small literature can be subdivided into two groups.

A first group of papers evolved within the literature on environmental evaluation. As an alternative to the conventional methods (such as contingent valuation, travel cost

[8] For reviews of this literature see Frey and Stutzer (2002), van Praag and Ferrer-I-Carbonell (2004), Frey (2008) or Diener and Biswas-Diener (2008).

[9] A comprehensive summary of the main findings can e.g. be found in Frey and Stutzer (2002).

[10] See, e.g. Frijters, Haisken-DeNew and Shields (2004).

models and hedonic approaches) the value of environmental goods (or bads) can be assessed using subjective well-being data. The idea behind this approach[11] is to regress a measure of subjective well-being on a number of likely determinants (including personal income) and a measure of the environmental good to be evaluated. The value of the environmental good can then be assessed on the basis of the rate of marginal substitution between income and the level of the environmental good. This approach has been used to assess the value of environmental quality (Welsch 2002, van Praag and Baarsma 2005, Welsch 2006, Rehdanz and Maddison 2008, MacKerron and Mourato 2009, Luechinger 2009, Ferreira and Moro 2010), urban regeneration schemes (Dolan and Metcalfe, 2008) and climate (Van der Vliert et al., 2004, Rehdanz and Maddison, 2005, Maddison and Rehdanz, 2011). A few papers yet applied the approach to the evaluation of natural disasters. Carroll, Frijters and Shields (2009) made an attempt at quantifying the costs of droughts in Australia throughout the period of 2001 to 2004. They find that at least in rural areas life satisfaction significantly decreases during droughts. Luechinger and Raschky (2009) apply the valuation method to flood disasters in a sample of 15 European countries and find a significant negative and robust effect on life satisfaction. The effect starts to decay one year after the disasters occurred and completely vanishes after two years. Kountouris and Remoundou (2011) are concerned with quantifying the welfare costs of wildfires in the mediterranean region and find life satisfaction of the rural population to be to be negatively affected. Rehdanz et al. (2013) study the effects of the Fukushima catastrophe and find a significantly negative effect on subjective wellbeing that turns out to be the larger, the closer individuals live to Fukushima.[12]

The second group of papers makes no attempt of monetizing the effect of disasters but directly focuses on the effects of disasters on economic well-being. Three papers belong into this group.

First, Kimball et al. (2006) use happiness data from the University of Michigan Consumer Survey to study the effects of two natural disasters. For the period of August to October 2005 the Michigan Survey included questions on happiness. For this period weekly data is available. The authors use the dataset to study the reaction of the respondents to two natural disasters which occurred throughout the sample period. The first disaster was Hurricane Katrina in August 2005, the second one a large earthquake in Pakistan in October 2005. The authors report a decrease in happiness in early September which lasted for 2-3 weeks and which was most pronounced in the

[11] For a detailed overview on the approach see, e.g., Welsch and Kühling (2009).

[12] The Fukushima event has also been analyzed by Goebel et al. (2013). However, different from Rehdanz et al. (2013) the authors study the effects of the Fukushima catastrophe on concerns of environmental protection in Germany. Goebel et al. (2013) report a strong increase in environmental concerns of Germans in the aftermath of the Fukushima event.

South Central region which was closest to the devastation of Katrina. The authors also found happiness to decrease after the Pakistan earthquake, thereby indicating that the respondents did not only care about disasters in their own country but also in places far away.

Second, Berger (2010) uses the 1986 wave of the German Socio-Economic Panel (SOEP) to study the reaction of the panel members to the Chernobyl disaster, which occurred in late April 1986.[13] Since each annual wave of the survey consists of interviews conducted in the period in between March and October, the data can be divided into two groups: respondents which completed the interview before and after the disaster. However, Berger (2010) finds no significant difference in self-reported life satisfaction when controlling for a bunch of socio-demographic control variables. Interestingly enough, the respondents interviewed after the Chernobyl disaster are significantly more concerned with environmental protection. Thus, although the respondents were well aware of the consequences of the disaster, this awareness did not result in a significant reaction of reported life satisfaction.

Third, Yamamura (2012) studies the long-term effects of the large earthquake in Kobe which occurred in 1995. In order to do so, Yamamura (2012) uses data from the Japanese General Social Surveys, which were conducted in Japan in between 2000 and 2008 almost annually. The surveys also include a question on perceived happiness and allow to draw conclusions on whether the respondents lived in the Kobe region when the earthquake unfolded. After controlling for various socio-demographic control variables Yamamura (2012) finds the survivors of the Kobe earthquake to be significantly happier than the respondents from other Japanese regions. The author concludes that surviving a large natural disaster has a long-lasting positive effect on subjective well-being.

We might conclude that the comparatively small literature on the effects of natural disasters on subjective well-being has yet mostly concentrated on studying single disaster events.[14] Moreover, these studies are not primarily concerned with the effects of disaster risk but focus on the short-term well-being-effect of natural disasters.

3 Data and Descriptive Statistics

In order to study the effect of perceived hurricane risk on subjective well-being we collect and combine information from two different data sources. First, we make use

[13] Different from the nuclear accident in Fukushima, the Chernobyl disaster was not triggered by a natural catastrophe. We nevertheless report the results here, because the effects are perceived quite similar to those of a natural disaster.

[14] The only exception is the multicountry panel study by Luechinger and Raschky (2009), covering floods in 15 European countries.

of micro-data from the integrated European (EVS) and World Values Survey (WVS). This survey is conducted in a large number of countries around the globe and contains information on both earlier discussed concepts of subjective well-being as well as numerous control variables. Second, in order to approximate (perceived) hurricane risk, we use data from a meteorological database: the Best Track Dataset of hurricanes provided jointly by a number of meteorological research institutes. In the following we describe both databases in more detail.

3.1 Integrated European and World Values Survey

The World Values Surveys build on the European Values Study (EVS), which was first carried out in 1981. While the first wave of the EVS covered 16 countries, primarily located in Europe, the survey was extended to more and more countries around the globe and developed into the World Values Survey in the course of time. Today the network of countries consists of more than 100 countries. At the time when this paper was written, 5 waves of the integrated EVS/WVS survey were available. As the early waves cover only a few and mostly European countries, we use the 3rd, the 4th- and the 5th wave of the integrated EVS/WVS survey, covering the years from 1995 to 2009.[15]

The EVS/WVS surveys have the advantage that they collect, inter alia, data for both concepts of subjective well-being discussed earlier: happiness and life satisfaction. With respect to happiness, individuals can state when "taking all things together" they are "very happy", "rather happy", "not very happy", or "not at all happy". Concerning life satisfaction, individuals are asked: "All things considered, how satisfied are you with your life as a whole these days?". Answers can be given within a range from 1 ("completely dissatisfied") to 10 ("completely satisfied"). Thus, the variable "happiness" has four categories, while "life satisfaction" has ten.

In order to take the heterogeneity of the respondents adequately into account and to control for the direct effects of hurricanes on individual well-being, we employ numerous control variables on the individual level in our estimation approach. Among them is the age and the gender of the respondent, the marital status (dummies for married, separated and widowed respondents), the employment status (dummies for unemployed, retired and studying respondents), the education level (dummy for highly educated respondents), individual income (dummies for respondents with low and high income) and the self-reported freedom of choice as a measure of the locus of control (Rotter, 1990). The choice of the control variables is based on the earlier cited empirical literature on the determinants of well-being. All employed control variables were taken from the EVS/WVS database.

[15]Tables 8 and 9 in the Appendix give an overview on the sample countries and periods.

3.2 Best Track Data of Hurricanes

Hurricanes are a specific and highly destructive form of storms.[16] They belong to the storm class of cyclones, which are defined as areas of low atmospheric pressure, characterized by rotating winds. As a consequence of the Coriolis effect, cyclones rotate counterclockwise in the Northern and clockwise in the Southern Hemisphere. Depending on their region of origin, cyclones are classified as tropical or extratropical. Tropical cyclones develop between 5 and 20 degrees latitude and thus over warm water. On the contrary, extratropical cyclones have cool central cores as they typically form between 30 and 70 degrees latitude in association with weather fronts. The two types of cyclones can have quite similar destructive effects, however, they differ in their source of energy and their structure. Tropical cyclones derive their energy from warm ocean water and heat of rising air which condenses and forms clouds. Extratropical cyclones derive their energy from the temperature difference of airmasses on both sides of a front.

According to the National Oceanic and Atmospheric Administration (NOAA) tropical cyclones with a maximum sustained wind of 38 mph (61 km/h) or less are called "tropical depressions". Whenever a tropical cyclone reaches winds of at least 39 mph (63 km/h) they are typically called "tropical storms". At this stage they are also assigned a name. If maximum sustained winds reach 74 mph (119 km/h), the cyclone is called a hurricane, whenever it developed in the North Atlantic Ocean, the Northeast Pacific Ocean east of the dateline or the South Pacific Ocean east of 160°E. In other regions the terms "typhoon" (Northwest Pacific Ocean west of the dateline), "severe tropical storm" (Southwest Pacific Ocean west of 160°E or Southeast Indian Ocean east of 90°E), and "severe cyclonic storm" (North Indian Ocean) are common. In the Southwest Indian Ocean the terminology sticks to the simple term "tropical cyclone".

Hurricanes (or more general tropical cyclones) are further classified according to their wind speed. This is often done by employing the Saffir Simpson Scale (see Table 1).[17] The Saffir Simpson Hurricane Wind Scale is a 1 to 5 rating based on the hurricane's intensity. This scale only addresses the wind speed and does not take into account the potential for other hurricane-related impacts such as storm surge and rainfall-induced floods. Earlier versions of this scale, known as the "Saffir Simpson Hurricane Scale", also incorporated these categories, however, often led to quite subjective and sometimes implausible categorizations of occurring storms. In order to reduce public confusion and to provide a more scientifically defensible scale, the storm surge ranges, flooding impact and central pressure statements were removed from the Saffir Simpson Scale and only peak winds are now employed.

[16] The following expositions are primarily based on Keller and DeVecchio (2012).

[17] The scale is named after its inventors, the wind engineer Herb Saffir and the meteorologist Bob Simpson.

Table 1: Saffir Simpson Hurricane Wind Scale

Category	Sustained Winds	Types of Damage Due to Hurricane Winds
1	74-95 mph 64-82 kt 119-153 km/h	Very dangerous winds will produce some damage: Well-constructed frame homes could have damage to roof, shingles, vinyl siding and gutters. Large branches of trees will snap and shallowly rooted trees may be toppled. Extensive damage to power lines and poles likely will result in power outages that could last a few to several days.
2	96-110 mph 83-95 kt 154-177 km/h	Extremely dangerous winds will cause extensive damage: Well-constructed frame homes could sustain major roof and siding damage. Many shallowly rooted trees will be snapped or uprooted and block numerous roads. Near-total power loss is expected with outages that could last from several days to weeks.
3	111-129 mph 96-112 kt 178-208 km/h	Devastating damage will occur: Well-built framed homes may incur major damage or removal of roof decking and gable ends. Many trees will be snapped or uprooted, blocking numerous roads. Electricity and water will be unavailable for several days to weeks after the storm passes.
4	130-156 mph 113-136 kt 209-251 km/h	Catastrophic damage will occur: Well-built framed homes can sustain severe damage with loss of most of the roof structure and/or some exterior walls. Most trees will be snapped or uprooted and power poles downed. Fallen trees and power poles will isolate residential areas. Power outages will last weeks to possibly months. Most of the area will be uninhabitable for weeks or months.
5	157 mph or higher 137 kt or higher 252 km/h or higher	Catastrophic damage will occur: A high percentage of framed homes will be destroyed, with total roof failure and wall collapse. Fallen trees and power poles will isolate residential areas. Power outages will last for weeks to possibly or higher months. Most of the area will be uninhabitable for weeks or months.

Source: http://www.nhc.noaa.gov/aboutsshws.php

The indicator of hurricane risk, we employ in our empirical analysis, is based on data from a meteorological database: the Best Track Dataset of tropical cyclones provided jointly by the National Oceanic and Atmospheric Administration (NOAA), the Tropical Prediction Center (Atlantic and eastern North Pacific hurricanes), and the Oceanography Center / Joint Typhoon Warning Center (Indian Ocean, western North Pacific, and Oceania hurricanes).[18] The advantage of this database is its worldwide coverage. The Best Track dataset provides data on the position of tropical cyclone centers in 6-hourly intervals[19] in its geographic coordinates, the measured maximal sustained wind speed in knots,[20] central surface pressure data in millibar and the Saffir Simpson Hurricane Wind Scale rating of the referring storm interval. The data is collected post-event from different sources like reconnaissance aircraft, ships and weather satellites.

Most of the time, hurricanes are located over the open sea. While tropical cyclones might cause some damage there, e.g. at oil platforms or ships, the referring storm periods are a thread to life and/or wealth for only a minimal fraction of the population. We therefore concentrate on storm periods occurring over land masses. Most of these storm periods are located in coastal areas. This is due to the fact that tropical cyclones rapidly diminish when a cyclone's eye passes land masses. Atop land masses a storm lacks moisture and heat provided by the ocean. As a consequence it quickly loses power and starts diminishing. However, as the destructive power of a tropical cyclone goes well beyond a cyclone's center we follow Yang's (2005) proposal to include all 6-hourly storm intervals with a Saffir-Simpson grading whose centers pass a country's borders up to a 160 kilometer distance. This buffer zone might be justified by the typical structure of tropical cyclones. Its strongest winds are located in the eyewall, a ring of tall thunderstorms located around the cyclone's eye. The eye is the calmest part of the tropical cyclone with a typical diameter of in between 32 and 64 kilometers. Around the eyewall and arranged like a spiral, there are curved rainbands producing heavy rain, wind and tornadoes. The destructive winds and rains of a tropical cyclone affect a wide area. Hurricane winds may extend to more than 242 kilometers from the eye of a large tropical cyclone. Because this extension may vary considerably from case to case, a cautious buffer of 160 kilometers seems to be reasonable.

Using the described Best Track Dataset we construct two different hurricane indicators: The first indicator (F) is the annual sum of all six-hourly storm intervals with a Saffir-Simpson grading whose centers pass a country's borders up to a 160 kilometer distance. Note that this indicator is not a pure frequency indicator of hurricanes, as

[18] The dataset was downloaded from the Unisys Weather Hurricane Data Archive at: http://weather.unisys.com/hurricane/index.php. For our purposes we used the tracking information files for each single hurricane provided in the annual storm tracking data.

[19] The data is recorded on a daily basis at 12am, 6am, 12pm, and 6 pm.

[20] The database contains the average maximum sustained wind speed at 10 metres above the earth's surface over a one minute time span anywhere within the tropical cyclone.

it bases on the number of six-hourly storm periods. Thus, storms which are located over landmasses for longer periods of time have a higher impact on the indicator than quickly decaying hurricanes. Moreover, more severe hurricanes are also more likely to exist for longer periods of time. For reasons of simplicity, we nevertheless refer to this indicator as "frequency indicator" in the following. The second hurricane indicator, we calculate for our empirical analysis, also incorporates storm severity. This indicator, we refer to as "severity indicator" in the following (S), is defined as the annual sum of Saffir-Simpson gradings of all six-hourly storm intervals whose centers pass a country's borders up to a 160 kilometer distance.

3.3 Descriptive Statistics of Combined Dataset

In the following we provide a brief overview on the combined dataset. Tables 2 and 3 report the mean values of the employed control variables for selected countries and the whole country sample.

Table 2: Variable means part I (selected countries)

Country	Life satisfaction	Happiness	Hurricane frequency (F)	Hurricane severity (S)	Female	Age	Children	Married	Separated	Widowed
Australia	7.47	3.33	18.34	45.57	0.53	45.79	0.70	0.63	0.10	0.07
Brazil	7.64	3.24	0.00	0.00	0.58	39.96	0.72	0.58	0.09	0.06
Canada	7.80	3.41	3.00	3.00	0.59	47.32	0.74	0.57	0.10	0.08
China	6.73	2.96	14.81	24.60	0.51	41.73	0.86	0.85	0.01	0.03
Colombia	8.31	3.33	1.34	1.67	0.49	36.37	0.71	0.60	0.06	0.03
Dominican Rep.	7.13	3.05	5.00	6.00	0.59	28.72	0.47	0.40	0.07	0.01
France	6.86	3.24	0.00	0.00	0.52	47.14	0.72	0.63	0.10	0.08
Germany	6.93	2.97	0.00	0.00	0.55	47.06	0.72	0.64	0.09	0.09
India	5.82	3.01	0.34	0.34	0.44	39.14	0.86	0.80	0.01	0.04
Indonesia	6.93	3.17	0.66	0.66	0.48	38.93	0.69	0.45	0.01	0.06
Japan	6.71	3.17	22.00	46.03	0.55	47.43	0.78	0.74	0.04	0.04
Mexico	7.90	3.24	22.13	40.47	0.50	37.09	0.73	0.60	0.06	0.05
Philippines	6.75	3.29	16.00	25.50	0.50	37.50	0.72	0.71	0.01	0.04
Puerto Rico	8.25	3.39	3.09	6.80	0.65	44.25	0.77	0.56	0.13	0.09
Viet Nam	6.86	3.25	3.60	6.00	0.50	41.47	0.80	0.75	0.01	0.04
Spain	6.97	3.05	0.00	0.00	0.51	45.82	0.67	0.61	0.03	0.08
Great Britain	7.57	3.32	0.00	0.00	0.52	45.74	0.52	0.59	0.09	0.09
United States	7.54	3.34	9.41	14.39	0.52	46.42	0.74	0.58	0.12	0.07
All sample countries	6.44	3.04	1.97	3.63	0.52	40.44	0.71	0.63	0.05	0.06

The average respondent in our sample is 40 years old, 12% of all respondents are retired. Our sample is almost balanced with respect to gender. Most respondents are married (63%), however, we also have numerous separated (5%) and widowed (6%) individuals in our sample. The share of respondents declaring to have at least one child amounts to 71%. By far the most respondents in our sample are actively working. However, 10% declare to be unemployed, 12% are retired and 8% are students. The income dummies for very low and very high incomes exhibit the typical skewness of the income distribution. While 38% declare to belong to one of the lowest three income classes, only 3% do so for the highest two classes. 15% of all respondents are highly educated. On average, individuals in the sample countries report a life

Table 3: Variable means part II (selected countries)

Country	Highly educated	Unemployed	Retired	Student	Low income	High income	Freedom of choice
Australia	0.15	0.01	0.24	0.04	0.37	0.09	0.86
Brazil	0.09	0.16	0.13	0.05	0.38	0.01	0.83
Canada	0.18	0.09	0.24	0.04	0.33	0.08	0.87
China	0.05	0.04	0.05	0.02	0.29	0.00	0.77
Colombia	0.17	0.11	0.02	0.07	0.47	0.05	0.88
Dominican Rep.	0.38	0.04	0.01	0.20	0.38	0.06	0.84
France	0.15	0.08	0.24	0.05	0.55	0.02	0.70
Germany	0.19	0.10	0.28	0.06	0.26	0.02	0.74
India	0.18	0.09	0.02	0.24	0.52	0.00	0.72
Indonesia	0.27	0.05	0.04	0.12	0.16	0.01	0.82
Japan	0.24	0.02	0.10	0.03	0.39	0.08	0.69
Mexico	0.12	0.06	0.03	0.08	0.43	0.07	0.87
Philippines	0.17	0.20	0.03	0.07	0.27	0.01	0.72
Puerto Rico	0.30	0.05	0.20	0.06	0.58	0.02	0.90
Viet Nam	0.05	0.05	0.10	0.02	0.11	0.00	0.78
Spain	0.11	0.09	0.19	0.06	0.32	0.01	0.72
Great Britain	0.11	0.06	0.22	0.05	0.21	0.21	0.84
United States	0.19	0.06	0.18	0.02	0.20	0.07	0.87
All sample countries	0.15	0.10	0.12	0.08	0.38	0.03	0.73

satisfaction of 6.44 and a happiness of 3.04 over the entire sample period. Tables 2 and 3 reveal a significant degree of country-variation in the control variables. Thus, a purely descriptive analysis is of little use.

Table 2 also reports on the two earlier described hurricane indicators. The displayed values indicate that hurricanes are comparatively rare events. The countries which are most concerned with hurricanes are Mexico, Japan, Australia, the Philippines, China and the United States. However, numerous additional countries also suffer from hurricane events. Figure 1 shows the distribution of hurricane events for the two earlier described hurricane indicators on an annual basis over the entire sample period. Obviously, both distributions are highly right-skewed. Thus, years with excessive hurricane periods (or severity) are comparatively rare.

4 Estimation Approach

The explanatory variables in our empirical analysis are the two earlier described measures of self-reported well-being. As both left-hand variables, happiness and life satisfaction, only have a few discrete ordered outcomes, the standard linear regression approach, employing the OLS technique, is inapplicable here. Instead we rely on the ordered logit approach for our empirical analysis, as it is usual in the related empirical literature.[21]

In order to study whether perceived hurricane risk has an influence on happiness

[21] For a detailed description of the ordered logit approach see Greene (2008), chapter 23. While Ferrer-i-Carbonell and Frijters (2004) argue that OLS estimations deliver similar results as logit estimations we stick to the methodologically more appropriate ordered logit estimation approach.

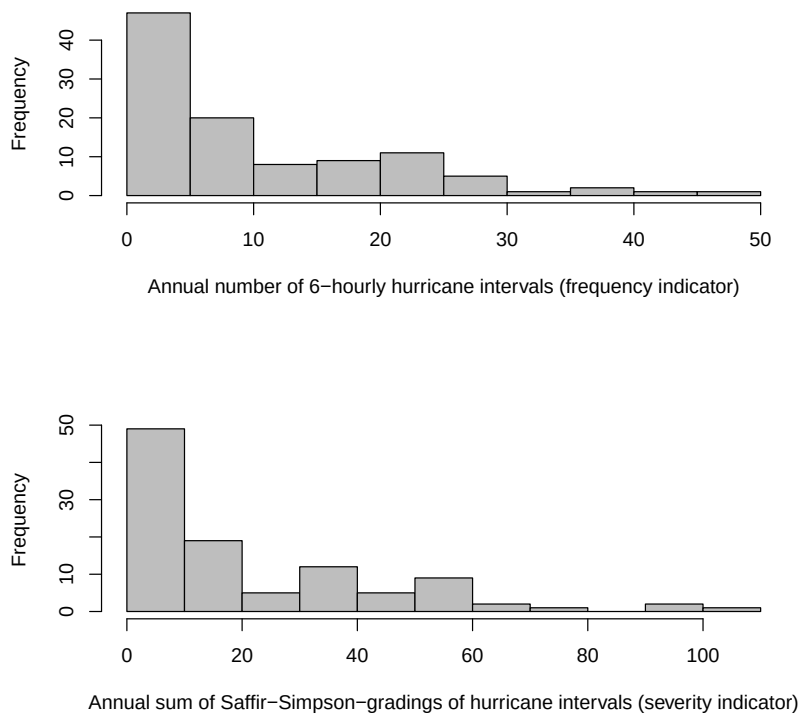

Figure 1: Distribution of hurricane indicators (zero values excluded)

and life satisfaction we regress both measures of well-being on (i) a suitable proxy of perceived hurricane risk and (ii) a number of additional control variables on the respondent-level. In order to control for country-specific effects (beyond differences in hurricane risk) we estimate the ordered logit model with country-fixed effects. Moreover, we allow for a common time-trend of the explanatory variable. The model to be estimated is thus given by

$$Prob\left(W_{i,j,t} = k\right) = Prob\left(\lambda_{k-1} < \alpha_j + \beta \cdot X_{i,j,t} + \gamma \cdot R_{j,t} + \delta \cdot t + \epsilon_{i,j,t} \leq \lambda_k\right), \tag{1}$$

where $W_{i,j,t}$ is well-being (happiness or life satisfaction) of individual i, living in country j. The variable t denotes time, $X_{i,j,t}$ is the vector of individual control variables and $R_{j,t}$ is the indicator of perceived hurricane risk in country j. We estimate the model using the maximum likelihood technique. However, in our estimation we have to consider that the measure of hurricane risk $R_{j,t}$ has the same value for all respondents from the same country and the same year. As Chamberlain (1980) and Ferrer-i-Carbonell and Frijters (2004) argue, the inclusion of macro-variables in microeconometric regressions requires to estimate the model with a clustered error term. We follow this procedure and estimate the ordered logit model using a robust maximum-likelihood procedure.

A central issue in our estimation approach is to construct a suitable proxy for perceived hurricane risk. While scientists around the globe work on complex hurricane prediction models and construct and publish hurricane risk maps, it seems to be quite

unlikely that the respondents to the integrated WVS/EVS evaluate this sort of information regularly. Psychologist argue that most individuals make use of comparatively simple rules of thumb when estimating the probability of future outcomes. Kahneman and Tversky (1973) and Kahneman, Slovic and Tversky (1982) have introduced the idea of subjective probability heuristics that lead to expectations which might differ systematically from the idea of rational expectations in the tradition of Muth (1961). This form of "bounded" rationality leads to the idea that individuals do not evaluate future options for action on the basis of objective probabilities of events but rather on subjective beliefs about these probabilities (Rabin 2002). Various heuristics have been discussed in the psychological literature, quite prominent among them the availability heuristics (Tversky and Kahneman, 1973). According to this heuristics individuals determine the likelihood of an event according to the ease with which they can recall instances matching the event. Thus, an individual's experiences and conditioning affects subjective expectations on how likely an event will occur. Chiodo et al. (2004) illustrate this heuristics at the example that the risk of burglary in a certain neighborhood will often be approximated by the number of burglaries one can recall from the past. In the remainder of this paper we follow this idea and assume that individuals base their assessment of hurricane risk on information on the frequency and/or the severity of hurricanes that occurred in the past in their country of origin, regardless of whether they were affected by these hurricanes themselves or collected their information on the disasters from the media.[22] As hurricanes typically have a high media coverage it seems to be reasonable to assume that an increasing number and/or an increasing severity of hurricanes in general will lead to the subjective perception of higher hurricane risk. However, it is less clear over which time-horizon individuals evaluate subjective hurricane risk. One might argue that individuals base their risk assessment only on the very recent past as they remember the most recent hurricanes best. However, as hurricanes are comparatively rarely occurring events, basing risk assessments on short periods of time leads to highly distorted risk assessments. One might therefore expect that even boundedly rational acting individuals evaluate hurricane risk over longer periods of time, e.g. take at least various years into account when making their assessment. As disaster risk is subject to change in the course of time, e.g. in consequence of changing climate conditions, and individuals are somewhat oblivious one might also expect that individuals do not consider the complete past when evaluating hurricane risk.

In the light of these considerations one might expect that most individuals will evaluate hurricane risk on at least a number of preceding years, maybe in between five and ten. However, as we cannot rule out shorter and even longer evaluation periods,

[22] Note that individuals might also be concerned with hurricanes when they live themselves in an region which they consider not to be hurricane-prone. This might be due to friends or relatives living in the affected regions, possible macroeconomic effects of hurricanes or altruism.

we generate a broad range of indicators of perceived hurricane risk and study how they perform in our estimation approach.

Within our empirical study we approximate perceived hurricane risk by the n-year-average of the two earlier described hurricane indicators. The hurricane risk measure R^F based on the frequency indicator F is thus defined as

$$R^F_{t,n} = \frac{\sum_{m=1}^{n} F_{t-i}}{n}.$$

Similarly, the hurricane risk measure R^S based on the severity indicator S is given by

$$R^S_{t,n} = \frac{\sum_{m=1}^{n} S_{t-i}}{n}.$$

Following the above expositions, we calculate both hurricane risk indicators for a wide range of evaluation periods ($n \in 1, 2, \ldots, 15$).

For both measures of well-being, we estimate the logit model from equation 1 for both (sets of) risk indicators.

5 Happiness and Hurricane Risk

In a first step, we study whether our indicators of perceived hurricane risk have an effect on happiness as the short-term component of self-reported well-being. Table 4 reports the logit estimation results for the risk measure R^F, derived from the hurricane frequency indicator.[23]

Model 1 reports the results of a baseline regression including all control variables except the hurricane risk indicator. Most of the included control variables turn out to have coefficients significantly different from zero. Moreover, the coefficients coincide with earlier findings in the happiness literature. Female respondents report higher happiness values than their male counterparts. Age has the typical u-shaped effect. Married respondents report higher happiness than singles, while the opposite holds true for separated and widowed respondents. Highly educated individuals are more happy than the rest. Unemployed individuals exhibit lower happiness than their employed counterparts. Retired respondents turn out to be less happy while students are more happy. We also find a significant effect of income on happiness. Individuals with high income are more and respondents with low income are less happy than individuals with medium-sized income. Finally, we find the locus of control to have a significant effect on self-reported happiness. Individuals reporting to have a high level of freedom of choice and control over their life tend to report significantly higher happiness.

[23]For reasons of clarity, we refrain from reporting the country-fixed effects and the time trend. The complete results are available from the author on request.

The models 2-5 include various versions of the frequency indicator of hurricane risk. The coefficients of the included control variables remain highly stable. With the exception of the five-year average of the frequency indicator, the estimated coefficients turn out to be negative. However, only the indicator based solely on the preceding period turns out to be significantly different from zero on the 90%-confidence level.

Table 5 reports the results for the alternative hurricane risk measure, derived from the hurricane severity indicator. Model 1 reports again the results of the baseline regression without hurricane risk indicator. Model 6 contains the severity indicator which is based solely on the preceding period. The models 7, 8 and 9 employ the five-year, the ten-year and the fifteen-year averaged severity indicator. Again, the hurricane risk measures deliver negative coefficients in three out of four cases. However, none of these coefficients is different from zero on conventional levels of confidence.

For reasons of clarity Tables 4 and 5 report only the results for a few variants of the frequency and the severity indicator. As we do not know exactly how individuals from their expectations on hurricane risk one might be interested in a systematic evaluation of the two indicators. In order to gain a more systematic picture of the effect of our two hurricane risk indicators on happiness we repeat our estimations for all averaging periods in between one and fifteen. The results of these estimations are summarized in Figure 2. The upper left diagram shows the estimated coefficients of the frequency indicators, the upper right diagram the estimates of the severity indicators. The two diagrams in the lower part of the figure display the p-values of the estimated coefficients.

With the exception of three cases, the frequency indicator delivers negative coefficients. However, only the short-sighted variants (the first lag, the two- and the three-year average) of the frequency indicator deliver a significantly negative coefficient. All indicator variants with longer memory turn out to be insignificant at conventional confidence levels. Thus, happiness tends only to be affected by hurricane risk, when we employ a risk indicator which is based on the very recent past. As explained earlier, these short-sighted risk indicators are comparatively poor measures of factual hurricane risk. However, as happiness is the more volatile and short-sighted component of well-being it seems to be reasonable that individuals report lower happiness values only if hurricanes occurred in the very recent past.

However, an inspection of the results from the estimations using the severity indicator of hurricane risk sows some seeds of doubt on the question, whether happiness is influenced by hurricane risk at all. As the right column of figure 2 indicates, none of the fifteen estimated coefficients turns out to be significantly different from zero.

Altogether, we find only weak empirical evidence in favor of the hypothesis that hurricane risk affects self-reported happiness. If at all, happiness is negatively affected by disasters which occurred in the very recent past. More reasonable hurricane risk

Table 4: Happiness and hurricane risk (based on frequency indicator)

	Model 1	Model 2 $n = 1$	Model 3 $n = 5$	Model 4 $n = 10$	Model 5 $n = 15$
Control variables					
Female (dummy)	0.1346***	0.1370***	0.1360***	0.1362***	0.1361***
	(0.0195)	(0.0197)	(0.0197)	(0.0197)	(0.0197)
Age	−0.0533***	−0.0533***	−0.0535***	−0.0535***	−0.0535***
	(0.0035)	(0.0036)	(0.0036)	(0.0035)	(0.0035)
Age squared	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Children (dummy)	0.0009	0.0007	−0.0019	−0.0002	−0.0003
	(0.0305)	(0.0311)	(0.0314)	(0.0313)	(0.0311)
Married (dummy)	0.4289***	0.4291***	0.4338***	0.4316***	0.4316***
	(0.0354)	(0.0359)	(0.0354)	(0.0358)	(0.0357)
Separated (dummy)	−0.2910***	−0.2899***	−0.2849***	−0.2871***	−0.2869***
	(0.0447)	(0.0451)	(0.0444)	(0.0447)	(0.0447)
Widowed (dummy)	−0.2452***	−0.2467***	−0.2402***	−0.2426***	−0.2425***
	(0.0394)	(0.0397)	(0.0396)	(0.0397)	(0.0396)
Highly educated (dummy)	0.1030***	0.1095***	0.1051***	0.1065***	0.1063***
	(0.0244)	(0.0247)	(0.0249)	(0.0247)	(0.0248)
Unemployed (dummy)	−0.3422***	−0.3395***	−0.3398***	−0.3397***	−0.3397***
	(0.0398)	(0.0400)	(0.0398)	(0.0399)	(0.0398)
Retired (dummy)	−0.0690**	−0.0693**	−0.0678**	−0.0684**	−0.0683**
	(0.0320)	(0.0321)	(0.0321)	(0.0320)	(0.0321)
Student (dummy)	0.0971***	0.0950***	0.0953***	0.0954***	0.0953***
	(0.0267)	(0.0267)	(0.0268)	(0.0271)	(0.0269)
Low income (dummy)	−0.3861***	−0.3833***	−0.3869***	−0.3864***	−0.3865***
	(0.0295)	(0.0300)	(0.0298)	(0.0301)	(0.0300)
High income (dummy)	0.2691***	0.2620***	0.2684***	0.2677***	0.2677***
	(0.0444)	(0.0438)	(0.0445)	(0.0441)	(0.0443)
Freedom of choice (dummy)	0.6442***	0.6399***	0.6403***	0.6402***	0.6402***
	(0.0353)	(0.0353)	(0.0353)	(0.0352)	(0.0352)
Number of hurricane periods...					
...1st lag		−0.0177*			
		(0.0103)			
...5-year avg.			0.0190		
			(0.0355)		
...10-year avg.				−0.0034	
				(0.0416)	
...15-year avg.					−0.0009
					(0.0460)
Num. obs.	133149	131092	131092	131092	131092
Pseudo R^2	0.2168	0.2187	0.2182	0.2181	0.2181
L.R.	28434.3209	28290.2263	28210.0875	28197.8000	28197.6134

Dependent variable: happiness
Ordered logit estimation (clustered standard errors)
Time trend and country-fixed effects not reported
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5: Happiness and hurricane risk (based on severity indicator)

	Model 1	Model 6 $n = 1$	Model 7 $n = 5$	Model 8 $n = 10$	Model 9 $n = 15$
Control variables					
Female (dummy)	0.1346***	0.1367***	0.1361***	0.1362***	0.1364***
	(0.0195)	(0.0196)	(0.0196)	(0.0197)	(0.0197)
Age	−0.0533***	−0.0534***	−0.0535***	−0.0535***	−0.0534***
	(0.0035)	(0.0036)	(0.0036)	(0.0035)	(0.0035)
Age squared	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Children (dummy)	0.0009	0.0003	−0.0037	−0.0001	0.0006
	(0.0305)	(0.0310)	(0.0316)	(0.0312)	(0.0312)
Married (dummy)	0.4289***	0.4299***	0.4355***	0.4315***	0.4309***
	(0.0354)	(0.0358)	(0.0353)	(0.0358)	(0.0359)
Separated (dummy)	−0.2910***	−0.2888***	−0.2831***	−0.2873***	−0.2885***
	(0.0447)	(0.0450)	(0.0443)	(0.0448)	(0.0450)
Widowed (dummy)	−0.2452***	−0.2453***	−0.2387***	−0.2428***	−0.2437***
	(0.0394)	(0.0396)	(0.0396)	(0.0397)	(0.0398)
Highly educated (dummy)	0.1030***	0.1083***	0.1040***	0.1068***	0.1076***
	(0.0244)	(0.0247)	(0.0249)	(0.0247)	(0.0247)
Unemployed (dummy)	−0.3422***	−0.3398***	−0.3401***	−0.3396***	−0.3394***
	(0.0398)	(0.0399)	(0.0398)	(0.0399)	(0.0399)
Retired (dummy)	−0.0690**	−0.0690**	−0.0671**	−0.0684**	−0.0690**
	(0.0320)	(0.0321)	(0.0320)	(0.0320)	(0.0321)
Student (dummy)	0.0971***	0.0946***	0.0954***	0.0954***	0.0958***
	(0.0267)	(0.0268)	(0.0268)	(0.0270)	(0.0270)
Low income (dummy)	−0.3861***	−0.3848***	−0.3866***	−0.3863***	−0.3854***
	(0.0295)	(0.0301)	(0.0297)	(0.0300)	(0.0299)
High income (dummy)	0.2691***	0.2651***	0.2671***	0.2680***	0.2681***
	(0.0444)	(0.0443)	(0.0442)	(0.0439)	(0.0443)
Freedom of choice (dummy)	0.6442***	0.6400***	0.6403***	0.6401***	0.6397***
	(0.0353)	(0.0353)	(0.0353)	(0.0352)	(0.0352)
Severity of hurricanes...					
...1st lag		−0.0068			
		(0.0063)			
...5-year avg.			0.0199		
			(0.0189)		
...10-year avg.				−0.0031	
				(0.0177)	
...15-year avg.					−0.0152
					(0.0154)
Num. obs.	133149	131092	131092	131092	131092
Pseudo R^2	0.2168	0.2183	0.2184	0.2181	0.2182
L.R.	28434.3209	28229.3809	28243.7013	28198.4032	28208.7898

Dependent variable: hapiness
Ordered logit estimation (clustered standard errors)
Time trend and country-fixed effects not reported
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

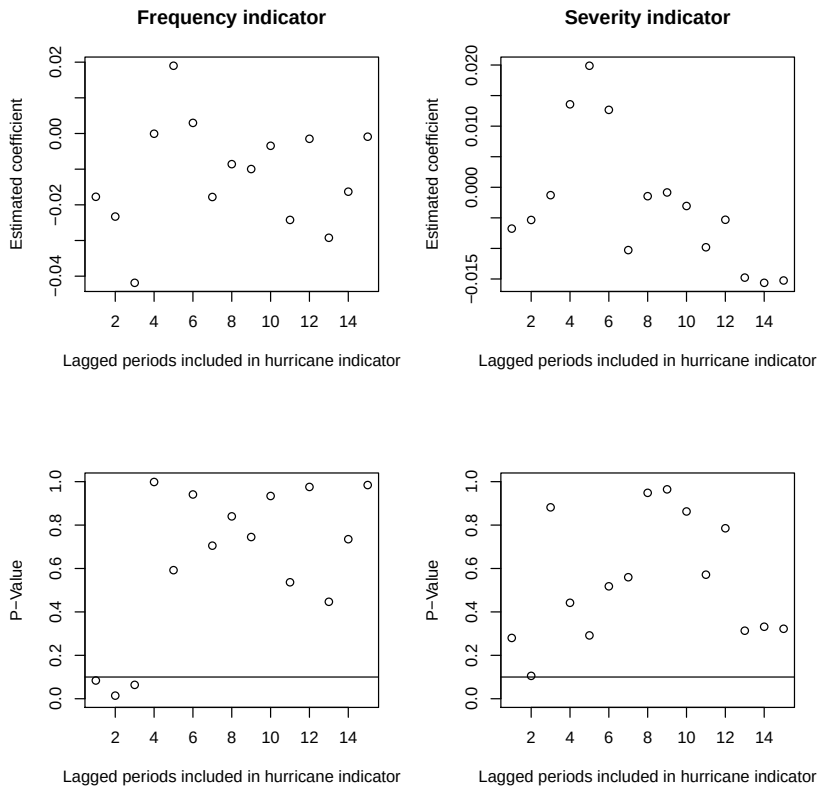

Figure 2: Estimated coefficients hurricane risk and happiness

measures, calculated on the basis of more than the three preceding years, tend to be unrelated to happiness. We therefore conclude that individuals tend to disregard hurricane risk in their assessment of current happiness.

Note that this conclusions does not imply that hurricanes have no systematic effect on individual happiness. As we already controlled for numerous factors through which natural disasters might directly affect individual happiness (such as e.g. income and unemployment) most of the earlier discussed direct effect of natural disasters is already captured by these controls.

6 Life Satisfaction and Hurricane Risk

In the next step of our analysis we study whether the two described measures of hurricane risk are related to self-reported life satisfaction, the second dimension of individual well-being.

Again, we start out with an analysis of the frequency indicator. The referring estimation results are shown in Table 6. Model 10 is the baseline estimation of the determinants of life satisfaction. We make use of the same set of control variables as in the earlier described happiness regressions. With the exception of the dummy variable

Table 6: Life satisfaction and hurricane risk (based on frequency indicator)

	Model 10	Model 11 $n = 1$	Model 12 $n = 5$	Model 13 $n = 10$	Model 14 $n = 15$
Control variables					
Female (dummy)	0.1068***	0.1078***	0.1077***	0.1081***	0.1079***
	(0.0156)	(0.0157)	(0.0157)	(0.0157)	(0.0157)
Age	−0.0469***	−0.0467***	−0.0468***	−0.0466***	−0.0466***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0032)
Age squared	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Children (dummy)	−0.0187	−0.0210	−0.0197	−0.0179	−0.0194
	(0.0293)	(0.0297)	(0.0296)	(0.0297)	(0.0297)
Married (dummy)	0.2830***	0.2819***	0.2803***	0.2804***	0.2809***
	(0.0344)	(0.0348)	(0.0350)	(0.0354)	(0.0351)
Separated (dummy)	−0.1583***	−0.1598***	−0.1612***	−0.1643***	−0.1622***
	(0.0389)	(0.0395)	(0.0396)	(0.0398)	(0.0398)
Widowed (dummy)	−0.0277	−0.0281	−0.0293	−0.0320	−0.0295
	(0.0398)	(0.0402)	(0.0404)	(0.0406)	(0.0405)
Highly educated (dummy)	0.0919***	0.0889***	0.0896***	0.0948***	0.0906***
	(0.0248)	(0.0250)	(0.0253)	(0.0252)	(0.0251)
Unemployed (dummy)	−0.3385***	−0.3363***	−0.3362***	−0.3349***	−0.3360***
	(0.0376)	(0.0377)	(0.0376)	(0.0378)	(0.0377)
Retired (dummy)	−0.0676**	−0.0688**	−0.0691**	−0.0713**	−0.0699**
	(0.0314)	(0.0316)	(0.0316)	(0.0315)	(0.0316)
Student (dummy)	0.0756**	0.0723**	0.0723**	0.0748**	0.0730**
	(0.0330)	(0.0331)	(0.0329)	(0.0323)	(0.0328)
Low income (dummy)	−0.4675***	−0.4665***	−0.4666***	−0.4639***	−0.4650***
	(0.0391)	(0.0396)	(0.0394)	(0.0392)	(0.0392)
High income (dummy)	0.3306***	0.3275***	0.3281***	0.3319***	0.3294***
	(0.0460)	(0.0462)	(0.0458)	(0.0458)	(0.0456)
Freedom of choice (dummy)	1.1366***	1.1325***	1.1327***	1.1310***	1.1317***
	(0.0490)	(0.0493)	(0.0493)	(0.0493)	(0.0493)
Number of hurricane periods...					
...1st lag		−0.0029			
		(0.0056)			
...5-year avg.			−0.0172		
			(0.0267)		
...10-year avg.				−0.0772***	
				(0.0198)	
...15-year avg.					−0.0624
					(0.0487)
Num. obs.	133718	131656	131656	131656	131656
Pseudo R^2	0.2768	0.2777	0.2777	0.2784	0.2779
L.R.	42675.9655	42184.7329	42194.2171	42312.7873	42229.2227

Dependent variable: life satisfaction
Ordered logit estimation (clustered standard errors)
Time trend and country-fixed effects not reported
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

for widowed individuals,[24] the baseline model delivers qualitatively the same results as the happiness models. Interestingly enough, the models explaining life satisfaction deliver systematically higher Pseudo R^2 values as the happiness regressions summarized in the previous section. Thus, the more far-sighted and thoughtful component of subjective well-being turns out to be more easily predictable than happiness.

Model 11 makes use of the frequency indicator, based on the preceding period. Models 12, 13 and 14 approximate hurricane risk by the 5-, the 10- and the 15-year frequency average. Again the estimated coefficients of the control variables remain almost unaffected by the inclusion of the risk measure. The estimated coefficients of the risk measure turn out be negative in all estimations. While the 1-, the 5- and the 15-year average turn out to be insignificant, the 10-year average is significant on the 99%-confidence-level.

When repeating the estimations for the severity indicator (see figure 7), the results are similar. Again, all estimated coefficients are negative. The 10-year average of the severity indicator is significant on the 99%-confidence-level. Moreover, the 15-year average of the severity indicator is now also significant, although only on the 90%-confidence-level.

Again we study the two hurricane risk indicators more systematically by repeating the estimations for all averaging periods in between one and fifteen. The results of these estimations are summarized in Figure 3. Interestingly enough, we find a systematic relation between life satisfaction and hurricane risk for both indicators for averaging periods exceeding six years. When using more than six years, the severity indicator always delivers significantly negative coefficients. A similar pattern exists for the frequency indicator, however, for averaging periods above 14 the indicator gets insignificant again. Moreover, when using more than six averaging periods, the estimated coefficients of the hurricane risk indicator increase in absolute size. In the light of the fact that especially those hurricane risk indicators which are based on the longer past turn out to be significantly negative we can rule out that this finding is driven by the direct effects of hurricanes on life satisfaction. Altogether, we thus find robust empirical evidence in favor of the hypothesis that hurricane risk has a significantly negative effect on life satisfaction.

[24] While we found widowed individuals to report significantly lower levels of happiness, we find no such effect for self-reported life satisfaction.

Table 7: Life satisfaction and hurricane risk (based on severity indicator)

	Model 10	Model 15 $n = 1$	Model 16 $n = 5$	Model 17 $n = 10$	Model 18 $n = 15$
Control variables					
Female (dummy)	0.1068***	0.1077***	0.1076***	0.1083***	0.1080***
	(0.0156)	(0.0157)	(0.0157)	(0.0157)	(0.0157)
Age	−0.0469***	−0.0468***	−0.0468***	−0.0465***	−0.0465***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0032)
Age aquared	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Children (dummy)	−0.0187	−0.0211	−0.0196	−0.0179	−0.0182
	(0.0293)	(0.0297)	(0.0297)	(0.0298)	(0.0298)
Married (dummy)	0.2830***	0.2821***	0.2805***	0.2806***	0.2804***
	(0.0344)	(0.0347)	(0.0350)	(0.0354)	(0.0353)
Separated (dummy)	−0.1583***	−0.1596***	−0.1612***	−0.1643***	−0.1636***
	(0.0389)	(0.0395)	(0.0397)	(0.0398)	(0.0399)
Widowed (dummy)	−0.0277	−0.0278	−0.0291	−0.0321	−0.0304
	(0.0398)	(0.0402)	(0.0404)	(0.0405)	(0.0406)
Highly educated (dummy)	0.0919***	0.0886***	0.0896***	0.0950***	0.0924***
	(0.0248)	(0.0250)	(0.0253)	(0.0251)	(0.0251)
Unemployed (dummy)	−0.3385***	−0.3364***	−0.3361***	−0.3349***	−0.3354***
	(0.0376)	(0.0376)	(0.0376)	(0.0378)	(0.0378)
Retired (dummy)	−0.0676**	−0.0687**	−0.0692**	−0.0711**	−0.0708**
	(0.0314)	(0.0316)	(0.0316)	(0.0316)	(0.0316)
Student (dummy)	0.0756**	0.0722**	0.0723**	0.0742**	0.0739**
	(0.0330)	(0.0330)	(0.0330)	(0.0325)	(0.0325)
Low income (dummy)	−0.4675***	−0.4668***	−0.4669***	−0.4643***	−0.4638***
	(0.0391)	(0.0396)	(0.0395)	(0.0391)	(0.0391)
High income (dummy)	0.3306***	0.3281***	0.3291***	0.3334***	0.3303***
	(0.0460)	(0.0460)	(0.0457)	(0.0458)	(0.0456)
Freedom of choice (dummy)	1.1366***	1.1326***	1.1328***	1.1311***	1.1312***
	(0.0490)	(0.0493)	(0.0493)	(0.0493)	(0.0493)
Severity of hurricanes...					
...1st lag		−0.0009			
		(0.0040)			
...5-year avg.			−0.0095		
			(0.0161)		
...10-year avg.				−0.0358***	
				(0.0072)	
...15-year avg.					−0.0394*
					(0.0210)
Num. obs.	133718	131656	131656	131656	131656
Pseudo R^2	0.2768	0.2777	0.2777	0.2785	0.2782
L.R.	42675.9655	42182.2214	42194.8294	42328.2826	42280.4157

Dependent variable: life satisfaction
Ordered logit estimation (clustered standard errors)
Time trend and country-fixed effects not reported
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

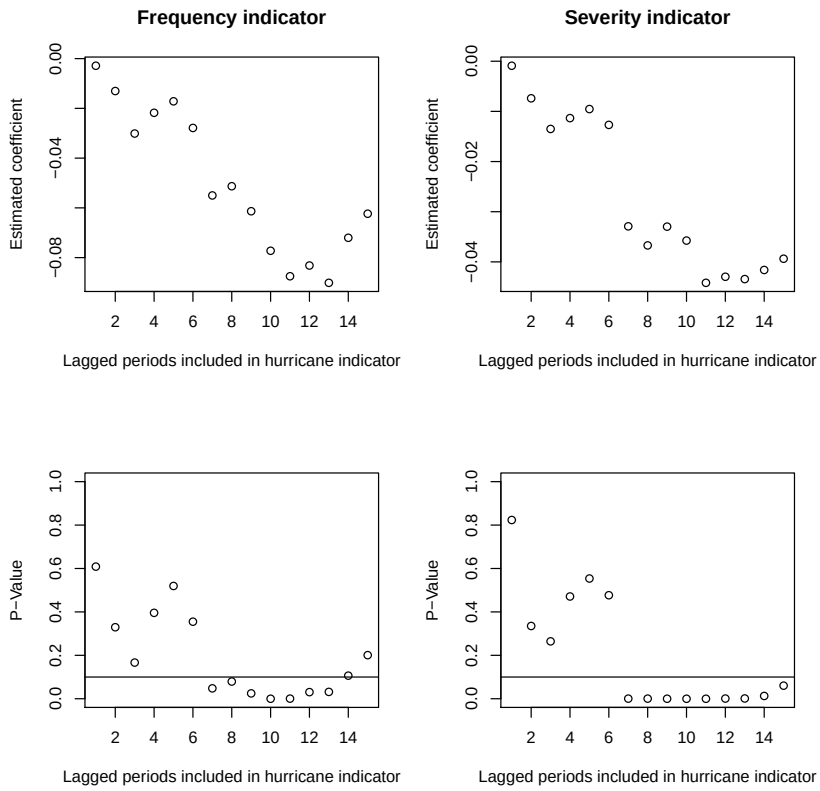

Figure 3: Estimated coefficients hurricane risk and life satisfaction

7 Influence of Hurricane Risk in Poor and Rich Countries

In the preceding analysis we implicitly assumed that the respondents from different sample countries do not differ in their perception of hurricane risk. However, as the population in poorer countries have much less possibilities to take protective measures against storms and policy interventions such as land-use regulations, building codes and engineering interventions are rare (Freeman et al. 2003), one might suspect that their individual well-being is closer related to disaster risk as this is the case in comparatively rich countries. In order to study this question we repeat our estimations for two subsamples of comparatively rich and poor countries. In order to subdivide the sample countries into appropriate groups we make use of the World Bank definition. Our group of relatively poor countries consists of countries falling into the categories of low-income and lower-middle income countries of the World Bank classification (altogether 17 countries). The remaining categories of upper-middle and high income countries make up our group of relatively rich countries (63 countries).

Figure 4 summarizes the estimation results. In fact we find much more pronounced effects of hurricane risk on life satisfaction in the group of comparatively poor countries. For both the frequency and the severity indicator the negative effects are larger in size,

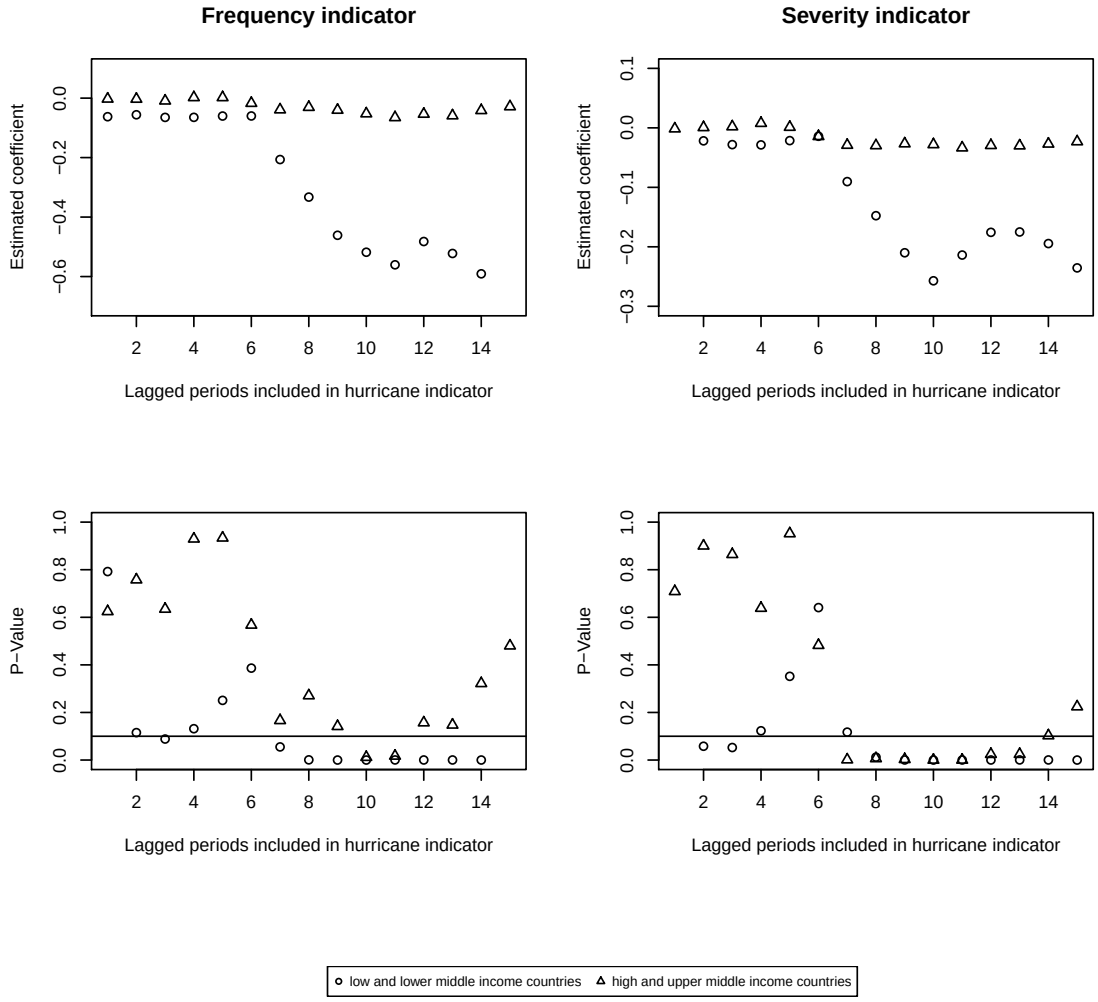

Figure 4: Effect of hurricane risk on life satisfaction in poor and in rich countries

especially when considering more than six preceding periods. When considering the frequency indicator, the estimated coefficients for the comparatively rich countries are only rarely significantly different from zero, whereas the opposite holds true for therelatively poor countries. When using the more sophisticated severity indicator the estimated coefficients for the group of comparatively poor countries is significant in by far the most cases, however even for the group of comparatively rich countries the estimated coefficients are significantly negative at least for the variants making use of more than six years.

Altogether, we might conclude that hurricane risk tends to depress life satisfaction especially in relatively poor countries, where the population has little possibilities to protect from hurricanes' consequences and can expect much less post-disaster support. However, at least when taking hurricane severity into account, we also find a negative (although much less pronounced) effect of hurricane risk on life satisfaction in higher

developed countries.

8 Conclusions

Throughout the last 20 years a growing number of scientists have expressed their worries about global warming. As global warming will likely affect the frequency and/or the severity of certain types of natural disasters, understanding the consequences of climate-induced disasters is urgently necessary. While most of the existing literature has yet primarily focused on the direct effects of natural disasters on economic growth, little attention has yet been devoted to the effect of natural disasters on individual well-being.

In this paper we focused on the effects of hurricane risk on the two most important measures of self-reported well-being, happiness and life satisfaction. The empirical evidence presented in this paper points into the direction that hurricane risk has little effect on perceived individual happiness, at least when controlling for the direct channels through which natural disasters might directly affect individual well-being. Thus, when evaluating the actual quality of their lives, individuals tend to disregard the risks of being affected by upcoming natural disasters. However, this holds not true when assessing their lives as a whole. We find robust empirical evidence in favor of the hypothesis that when making this more cognitive assessment, individuals tend to take hurricane risk into account and report lower degrees of life satisfaction when perceived hurricane risk is high. We conclude that the effects of natural disasters thus go well beyond the direct growth effects. Whenever the process of global warming increases natural disaster risk, this risk itself is an additional burden for the population, exposed to this risk. This holds true especially for comparatively poor countries in which the population can protect much worse against the consequences of hurricanes and can also expect less post-hurricane support.

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Appendix

Table 8: Country sample (part I)

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
Albania	0	0	0	999	0	0	0	1000	0	0	0	0
Algeria	0	0	0	0	0	0	0	1282	0	0	0	0
Andorra	0	0	0	0	0	0	0	0	0	0	1003	0
Argentina	1079	0	0	0	1280	0	0	0	0	0	0	1002
Armenia	0	0	2000	0	0	0	0	0	0	0	0	0
Australia	2048	0	0	0	0	0	0	0	0	0	1421	0
Azerbaijan	0	0	2002	0	0	0	0	0	0	0	0	0
Bangladesh	0	1525	0	0	0	0	0	1500	0	0	0	0
Belarus	0	2092	0	0	0	0	0	0	0	0	0	0
Bosnia	0	0	0	800	0	0	1200	0	0	0	0	0
Brazil	0	0	0	0	0	0	0	0	0	0	0	1500
Bulgaria	0	0	1072	0	0	0	0	0	0	0	1001	0
Canada	0	0	0	0	0	1931	0	0	0	0	0	2164
Chile	0	1000	0	0	0	1200	0	0	0	0	0	1000
China	1500	0	0	0	0	0	1000	0	0	0	0	0
Colombia	0	0	3029	2996	0	0	0	0	0	0	3025	0
Croatia	0	1196	0	0	0	0	0	0	0	0	0	0
Cyprus	0	0	0	0	0	0	0	0	0	0	0	1050
Dominican Rep.	0	417	0	0	0	0	0	0	0	0	0	0
Egypt	0	0	0	0	0	0	3000	0	0	0	0	0
El Salvador	0	0	0	0	1254	0	0	0	0	0	0	0
Estonia	0	1021	0	0	0	0	0	0	0	0	0	0
Finland	0	987	0	0	0	0	0	0	0	0	1014	0
France	0	0	0	0	0	0	0	0	0	0	0	1001
Georgia	0	2008	0	0	0	0	0	0	0	0	0	0
Germany	0	0	2026	0	0	0	0	0	0	0	0	2064
Great Britain	0	0	0	1093	0	0	0	0	0	0	1041	0
Guatemala	0	0	0	0	0	0	0	0	0	1000	0	0
Hong Kong	0	0	0	0	0	0	0	0	0	0	1252	0
Hungary	0	0	0	650	0	0	0	0	0	0	0	0
India	2040	0	0	0	0	0	2002	0	0	0	0	2001
Indonesia	0	0	0	0	0	0	1000	0	0	0	0	2015
Iran	0	0	0	0	0	2532	0	0	0	0	0	0
Iraq	0	0	0	0	0	0	0	0	0	2325	0	2701
Israel	0	0	0	0	0	0	1199	0	0	0	0	0
Italy	0	0	0	0	0	0	0	0	0	0	1012	0
Japan	0	0	0	0	0	1362	0	0	0	0	1096	0
Jordan	0	0	0	0	0	0	1223	0	0	0	0	0
Kyrgyzstan	0	0	0	0	0	0	0	0	1043	0	0	0
Latvia	0	1200	0	0	0	0	0	0	0	0	0	0
Lithuania	0	0	1009	0	0	0	0	0	0	0	0	0
Macedonia	0	0	0	995	0	0	1055	0	0	0	0	0
Malaysia	0	0	0	0	0	0	0	0	0	0	0	1201
Mexico	854	1510	0	0	0	1535	0	0	0	0	1560	0
Moldova	0	984	0	0	0	0	0	1008	0	0	0	1046
Montenegro	0	240	0	0	0	0	1060	0	0	0	0	0
Morocco	0	0	0	0	0	0	1251	0	0	0	0	0

Table 9: Country sample (part II)

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
Netherlands	0	0	0	0	0	0	0	0	0	0	0	1050
New Zealand	0	0	0	1201	0	0	0	0	0	954	0	0
Nigeria	1996	0	0	0	0	2022	0	0	0	0	0	0
Norway	0	1127	0	0	0	0	0	0	0	0	0	0
Pakistan	0	0	733	0	0	0	2000	0	0	0	0	0
Peru	0	1211	0	0	0	0	1501	0	0	0	0	1500
Philippines	0	1200	0	0	0	0	1200	0	0	0	0	0
Poland	0	0	1153	0	0	0	0	0	0	0	1000	0
Puerto Rico	1164	0	0	0	0	0	720	0	0	0	0	0
Romania	0	0	0	1239	0	0	0	0	0	0	1776	0
Russia	2040	0	0	0	0	0	0	0	0	0	0	2033
Saudi Arabia	0	0	0	0	0	0	0	0	1502	0	0	0
Serbia	0	1280	0	0	0	0	1200	0	0	0	0	0
Serbia and Montenegro	0	0	0	0	0	0	0	0	0	0	1220	0
Singapore	0	0	0	0	0	0	0	1512	0	0	0	0
Slovakia	0	0	0	1095	0	0	0	0	0	0	0	0
Slovenia	1007	0	0	0	0	0	0	0	0	0	1037	0
South Africa	0	2935	0	0	0	0	3000	0	0	0	0	2988
South Korea	0	1249	0	0	0	0	1200	0	0	0	1200	0
Spain	1211	0	0	0	0	1209	0	0	0	0	0	0
Sweden	0	1009	0	0	1015	0	0	0	0	0	0	1003
Switzerland	0	1212	0	0	0	0	0	0	0	0	0	0
Taiwan	0	0	0	0	0	0	0	0	0	0	0	1227
Tanzania	0	0	0	0	0	0	1171	0	0	0	0	0
Trinidad and Tobago	0	0	0	0	0	0	0	0	0	0	0	1002
Turkey	0	1907	0	0	0	0	3401	0	0	0	0	0
Uganda	0	0	0	0	0	0	1002	0	0	0	0	0
Ukraine	0	2811	0	0	0	0	0	0	0	0	0	1000
United States	1542	0	0	0	1200	0	0	0	0	0	0	1249
Uruguay	0	1000	0	0	0	0	0	0	0	0	0	1000
Venezuela	0	1200	0	0	0	1200	0	0	0	0	0	0
Viet Nam	0	0	0	0	0	0	1000	0	0	0	0	1495
Zimbabwe	0	0	0	0	0	0	1002	0	0	0	0	0