David Döhrmann

Impact Assessment of Natural Disasters on Reconstruction Costs

An Empirical Analysis

Cuvillier Verlag Göttingen
Internationaler wissenschaftlicher Fachverlag

Impact Assessment of Natural Disasters on Reconstruction Costs
– An Empirical Analysis –

Dissertation

submitted to the

Carl-Friedrich Gauß Department
University of Braunschweig – Institute of Technology

and the

Department of Civil and Environmental Engineering
University of Florence

in candidacy for the degree of a
Doktor der Wirtschaftswissenschaften (Dr. rer. pol.) /
Dottore di Ricerca in "Mitigation of Risk due to Natural Hazards on Structures and Infrastructures"*)

by
David Döhrmann
Born 11.12.1984
from Braunschweig, Germany

2015

*) Either the German or the Italian form of the title may be used.

Impact Assessment of Natural Disasters on Reconstruction Costs
– An Empirical Analysis –

Der
Carl-Friedrich-Gauß-Fakultät
der Technischen Universität Carolo-Wilhelmina zu Braunschweig

zur Erlangung des Grades eines
Doktors der Wirtschaftswissenschaften (Dr. rer. pol.)

vorgelegte Dissertation

von
David Döhrmann
geboren am 11.12.1984
in Braunschweig

Eingereicht am:	06.03.2015
Disputation am:	11.05.2015
1. Referent:	Prof. Dr. Marc Gürtler
2. Referent:	Prof. Dr. Marcello Galeotti

2015

Bibliografische Information der Deutschen Nationalbibliothek
Die Deutsche Nationalbibliothek verzeichnet diese Publikation in der Deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über http://dnb.d-nb.de abrufbar.
1. Aufl. - Göttingen : Cuvillier, 2015
Zugl.: (TU) Braunschweig, Univ., Diss., 2015

Nonnenstieg 8, 37075 Göttingen
Telefon: 0551-54724-0
Telefax: 0551-54724-21
www.cuvillier.de

1. Auflage, 2015
Gedruckt auf umweltfreundlichem, säurefreiem Papier aus nachhaltiger Forstwirtschaft.

ISBN 978-3-7369-9019-7
eISBN 978-3-7369-8019-8

Technische Universität Braunschweig

UNIVERSITÀ DEGLI STUDI FIRENZE

Zusammenfassung der Dissertation:

Impact Assessment of Natural Disasters on Reconstruction Costs – An Empirical Analysis –

In den vergangenen Jahrzehnten hat sowohl die Intensität als auch die Frequenz von Naturkatastrophen deutlich zugenommen. In diesem Zusammenhang kann beobachtet werden, dass nach Naturkatastrophen die Preise im Bausektor oftmals sprunghaft ansteigen. Ein begrenztes regionales Angebot an Arbeitskräften und Bauprodukten steht in der Regel einer rapide gestiegenen Nachfrage gegenüber, die temporär nicht befriedigt werden kann. Als Konsequenz sehen sich die wesentlichen Schadensträger (Staaten, Versicherungen, betroffene Individuen und Unternehmen) signifikant gestiegenen Kosten ausgesetzt. In Einzelfällen kann das Preisniveau bei Wiederaufbau lokal sogar um bis zu 60% gegenüber dem Preisniveau vor der Naturkatastrophe ansteigen. Dieses Phänomen wird auch als Demand Surge Effekt bezeichnet. Trotz der enormen Preissteigerungen und der damit verbundenen steigenden Kosten gibt es in der bestehenden Literatur jedoch kaum Ansätze zur Beschreibung und Quantifizierung von Demand Surge Effekten. Ein Hauptproblem besteht dabei darin, dass die lokale Entwicklung der Preise für Baudienstleistungen und Bauprodukte im Nichtkatastrophenfall nicht beobachtbar ist. Daher gestaltet es sich schwierig, die katastrophenbedingte Entwicklung der Preise von anderen Einflussfaktoren zu isolieren und darauf aufbauend zu erklären.

Vor diesem Hintergrund besteht das Ziel der vorliegenden Dissertation darin, zunächst einen Ansatz zur Quantifizierung von Demand Surge Effekten zu entwickeln. Dabei liegt der Fokus auf den Preisen für Baudienstleistungen, da Preise für Bauprodukte gewöhnlich keine Reaktionen auf das Eintreten einer Naturkatastrophe zeigen. Darauf aufbauend wird untersucht, unter welchen Bedingungen Naturkatastrophen signifikante Demand Surge Effekte induzieren. Schließlich besteht ein weiteres Ziel der Dissertation darin, die Stärke des Demand Surge Effektes über ein empirisches Modell zu erklären. Um diese Fragestellungen zu analysieren, wird in Kapitel 2 zunächst die Frage erörtert, was eine Naturkatastrophe charakterisiert und welche verschiedenen Typen von Schäden im Rahmen einer Naturkatastrophe zu unterscheiden sind. Anschließend wird in Kapitel 3 eine Einführung in das Thema Demand Surge gegeben. Zu diesem Zweck werden zunächst verschiedene Definitionen aus der bestehenden Literatur vorgestellt und ein Überblick über Naturkatastrophen gegeben, die in der Vergangenheit zu Demand Surge Effekten geführt haben. Zusätzlich werden die bestehenden Modelle zur Modellierung von Demand Surge Effekten vorgestellt und der entwickelte Ansatz zur Quantifizierung des Demand Surge Effektes formaltheoretisch hergeleitet. Dieser wird in Kapitel 4 in eine empirisch messbare Variante überführt und verwendet, um verschiedene Einflussfaktoren auf den Demand Surge Effekt zu bestimmen. Auf Basis zweier Datensätze zu Naturkatastrophen in den USA wird nachgewiesen, dass sowohl der Schaden der Naturkatastrophe selber, als auch zeitlich vor- und nachgelagerte Schäden alternativer Naturkatastrophen in geringer Entfernung zu signifikant höheren Demand Surge Effekten führen. Eine signifikant positive Beziehung kann zudem zwischen der Anzahl Versicherungsfälle beziehungsweise der Änderung des Bruttoinlandsprodukts im Bausektor und dem Demand Surge Effekt gezeigt werden. Dahingegen wird für Preissteigerungen im Baudienstleistungsbereich in den Monaten vor Eintritt der Naturkatastrophe ein negativer Effekt festgestellt. Kapitel 5 präzisiert diese Ergebnisse, indem die Frage nach möglichen Einflussfaktoren auf den De-

mand Surge Effekt in einem zweistufigen Verfahren untersucht wird. Zu diesem Zweck wird zunächst untersucht, unter welchen ökonomischen und katastrophenspezifischen Rahmenbedingungen signifikante Demand Surge Effekte beobachtet werden können. Für die Teilmenge der Beobachtungen mit einem signifikanten Demand Surge Effekt wird sodann untersucht, welche Faktoren die Stärke des Effektes erklären. In Ergänzung zu den in Kapitel 4 betrachteten Einflussfaktoren werden zudem in beiden Schritten der Analyse weitere ökonomische Faktoren in die Analyse integriert. So führen eine höhere Arbeitsauslastung im Bausektor der Katastrophenregion sowie ein geringeres Preisniveau für Baudienstleistungen im Zentrum der Katastrophe im Vergleich zu den umliegenden Regionen jeweils ceteris paribus zu höheren Demand Surge Effekten. Eine höhere Arbeitslosenquote in der Katastrophenregion verringert dagegen die Stärke des Effektes. In einem Ergebnisvergleich beider Schritte der Analyse stellt sich heraus, dass fast alle Einflussfaktoren sowohl die Wahrscheinlichkeit des Auftretens als auch die Stärke eines erheblichen Demand Surge Effektes beeinflussen. Eine Ausnahme in dieser Hinsicht bildet die Anzahl der Versicherungsfälle einer Naturkatastrophe. Diese ist lediglich dazu geeignet, die Wahrscheinlichkeit des Auftretens eines erheblichen Demand Surge Effektes zu erklären.

Acknowledgement

This monograph was written during my time as a scholarship holder at the International Graduate College 802 (IGC 802) “Risk Management of Natural and Civilization Hazards on Buildings and Infrastructure“ which was sponsored by the German Research Foundation (DFG), and my time as a research associate at the Department of Finance at the Technische Universität Braunschweig. First of all, I would like to thank my tutors Prof. Dr. Marc Gürtler and Prof. Dr. Marcello Galeotti for their support and commitment regarding my research work. They gave me the necessary freedom and had always the time to discuss about scientific problems. Concerning my time at the IGC 802, it was inspiring to work together with researchers from several fields of research and nations. Moreover, I had the opportunity to work several months at the Università degli Studi di Firenze and enjoyed this time a lot. My former flatmates Dr. Giovanni Michelazzo and M. Sc. Tommaso Massai helped me a lot during these days and taught me the italian way of life. Mille grazie! Of course, this would not have been possible without the help of the administrative team of the IGC 802. Mrs. Yvonne Wissmann and Dr. Matthias Reininghaus organized everything perfectly.

I spent most of my research time at the Department of Finance and would like to thank the whole team for several discussions regarding all kind of topics and the nice working atmosphere. Especially my former officemate Dr. Christine Winkelvos helped me a lot during my first years and shared with me the opportunity to be part of the IGC 802. Furthermore, I thank my co-author Dr. Martin Hibbeln for several joint research projects and publications. He always motivated me and was an excellent sparring partner during many discussions. Many thanks go to Silvia Nitschke. She helped me all the time with administrative problems and organized the department in an incredible manner. In addition, I thank Stefan Metzner who solved my IT-related problems at any time.

As a non native speaker this monograph needs some proofreading. I thank Dipl.-Math. Oec. Lina von Altenbockum, M. Sc. Simon Döhrmann, and Dipl.-Math. Oec. Matthias Kamrau for helpful comments and suggestions.

Last but not least I owe sincere thankfulness to my family. My parents Jürgen and Monika Döhrmann always supported and encouraged me to take the next step. They fostered my inquisitiveness and share with me the joy at new experiences and challenges. Also my siblings Simon and Laura Döhrmann assisted me during the preparation of this monograph. Special thanks go to Lina von Altenbockum for her patience and encouragement. She always had a critical view and, therefore, improved this work a lot.

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Nomenclature

Abbreviations

A.C.	Air Conditioning
Adj.	Adjusted
AIC	Akaike Information Criterion
AIR	Applied Insurance Research
AL	Alabama
ALE	Additional living expenses
ARIO	Adaptive Regional Input-Output
Avg.	Average
BEA	Bureau of Economic Analysis
BLS	Bureau of Labor Statistics
b	Billion
Cat.	Category
	Catastrophe
cf.	Confer
CPI	Consumer Price Index
CRED	Centre for Research on the Epidemiology of Disasters
CSH	Cultural, social, historical
Dam.	Damages
Dem.	Demand
Dist.	Distance
DKK	Danish crown
EAR	Economic Amplification Ratio
e.g.	Exempli gratia
EIOPA	European Insurance and Occupational Pensions Authority
Est.	Establishments
et al.	Et alii
ff.	Following pages

FL	Florida
FPHLM	Florida Public Hurricane Loss Model
FRED	Federal Reserve Economic Data
GA	Georgia
GDP	Gross Domestic Product
GDV	Gesamtverband der Deutschen Versicherungswirtschaft
GRIP	Global Risk Identification Program
	Global Risk Information Platform
hr	Hour
IA	Iowa
i.e.	Id est
IGC	International Graduate College
Inc.	Incorporated
ISO	International Standards Organisation
	Insurance Services Office
km	Kilometer
LA	Louisiana
Max.	Maximum
Min.	Minimum
MS	Mississippi
MSA	Metropolitan Statistical Area
NBER	National Bureau of Economic Research
NC	North Carolina
NFIP	National Flood Insurance Program
No.	Number
Obs.	Observations
OLS	Ordinary Least Squares
p.	Page
PCS	Property Claims Services
PECI	Post-event Claims Inflation
PLA	Post Catastrophe Loss Amplification
Prev.	Previous
Q	Quarter
QCEW	Quarterly Census of Employment and Wages
RMS	Risk Management Solutions
SC	South Carolina
SHELDUS	Spatial Hazard Events and Losses Database for the United States
Std. Dev.	Standard Deviation

Subsq.	Subsequent
Subst.	Substantial
TX	Texas
UN	United Nations
UNDP	United Nations Development Programme
Unemp.	Unemployment
US	United States
USAID	United States Agency for International Development
USD	US-Dollar
VA	Virginia
vs.	Versus
WGS	World Geodetic System
yr	Year

Mathematical Symbols

$1_{\{\}}$	Indicator variable
a	Point in time relative to the considered catastrophe
A	Region
$arccos$	Inverse cosine function
b	Point in time relative to the considered catastrophe
B	Region
c	Constant
c_{cat}	Expenses of building contractors in case of a catastrophe
C_i	Estimated replacement cost for property i
cos	Cosine function
d	Differential
$DS(\cdot)$	Degree to which an event would produce Demand Surge as a function of total societal loss
e	Euler's number, e = 2.7182...
e_i	Intensity of excitation at property i
$E(\cdot)$	Expectation value
$f(\cdot)$	Function
$F(\cdot)$	Cumulative distribution function
	Link function
i	Index
$i(t)$	Number of settled claims at time t

j	Counter
k	Counter
L	Ground-up loss
	Distance between region A and B
ln	Natural logarithm
p	Level of significance
p_1	Parameter
p_2	Parameter
$p(t)$	Wage level at time t
p_{cat}	Wage level in catastrophe scenario
$p_{no\text{-}cat}$	Wage level in no-catastrophe scenario
$\Delta p(t)$	Absolute Demand Surge at time t
Δp_{max}	Maximum absolute Demand Surge
$P(\cdot)$	Maximum effect of Demand Surge as a function of excitation
	Probability
$P(1,T)$	Vector of wage levels at points in time t = 1, ..., T
$P_{cat}(1,T)$	Vector of wage levels at points in time t = 1, ..., T
	in catastrophe scenario
$P_{no\text{-}cat}(1,T)$	Vector of wage levels at points in time t = 1, ..., T
	in no-catastrophe scenario
r	Capital costs
R^2	Coefficient of determination
sin	Sine function
t	Point in time
T	Estimated societal-level total loss
	Date of last damage repair/settled claim
$V(\cdot)$	Market value
x	Realization of covariates
x_i	Independent variable
$x(t)$	(Realized) demand quantity of workers at time t
X	Set of covariates
$y_i(\cdot)$	Mean damage factor of property i as a function of excitation
Y	Random variable
z	Variable
$z(t)$	Wage payments at time t
β	Coefficient vector
β_j	Coefficient of independent variable j

$\Delta\pi(t)$	Relative Demand Surge at time t
ζ	Increase in market value of wage payments when switching from a no-catastrophe to a catastrophe scenario
$\lambda_{A,B}$	Longitude of region A/B
$\Lambda(\cdot)$	Logistic cumulative distribution function
μ	Mean value
ξ	Auxiliary variable
ρ	Percentage of total repair costs attributable to labor costs
σ	Standard deviation
$\phi_{A,B}$	Latitude of region A/B
Φ	Information set at time t = 0
∂	Partial derivative

1 Introduction

1.1 Problem Definition and Objectives of This Work

In recent decades the frequency and severity of natural disasters increased.[1] This development is accompanied by an increase in catastrophe related economic losses and is assumed to continue for the foreseeable future if effective disaster mitigation efforts are omitted.[2] Due to the massive destruction of physical assets the basis for economic losses are generally reconstruction costs, which must be raised after a catastrophe to restore the original state of buildings and infrastructure. Thus, the need for reconstruction together with the financial influx from disaster relief and insurance payouts might create a boom.[3] As a consequence some economic sectors might even experience positive effects after natural disasters, e.g., retail and construction.

The sudden increase in demand is often confronted with a constant supply of relevant goods and labor. As a consequence, significant price effects for reconstruction labor and material are expected, which should be taken into account in the forecast of economic and insured losses of future catastrophes. Thus, to estimate future costs it is not appropriate to apply the expected price level under normal conditions. In literature such inflation or price effects are known as the "Demand Surge" effect and "occur[s] when the demand for products and services exceeds the regional capacity to efficiently supply them. The additional costs for these products and services are directly passed on to the consumer

[1] See Kunreuther and Michel-Kerjan (2009).
[2] See Pielke (2005) and Pielke et al. (2008).
[3] See Guimaraes et al. (1993).

(and the insurer)".[4] To provide some anecdotal evidence, it is estimated that the Demand Surge effect due to Hurricane Katrina is in the range of 30% to 40%, resulting in a significant increase in repair costs.[5] Moreover, Demand Surge is neither a new phenomenon nor limited to a particular region or a particular type of catastrophe.[6] First evidence of Demand Surge date back to the fourteenth century England, it has been observed all over the world and for several catastrophe types, like earthquakes, floods, hurricanes or wildfires.[7]

Against this background, it is quite remarkable that only a few contributions in the literature address this phenomenon. The scientific literature considers Demand Surge exclusively on a qualitative level or only for a specific catastrophe type or event; universally valid quantitative models for Demand Surge have not been published. In contrast, the main catastrophe modeling companies in the world consider the Demand Surge effect within the framework of modeling direct losses due to catastrophes. However, the models of these companies are not publicly available. In particular, it is not clear which empirical results underlie their models. Therefore, this thesis investigates the impact of catastrophe induced exogenous shocks to the local reconstruction industry. The most important research questions addressed are the following:

- How can Demand Surge effects be measured?
- Under which conditions do natural disasters lead to Demand Surge effects?
- How strong is the Demand Surge effect?

The above stated three research questions are studied with empirical analyses. First, some fundamentals of catastrophe risk and basics regarding the Demand Surge effect are presented. On the basis of these considerations two empirical research projects are carried out. The first analysis deals with the question how Demand Surge effects can be measured and identifies key drivers of this phenomenon. The second empirical analysis further

[4] See EQECAT (2005).
[5] See Munich Re (2006b).
[6] See Olsen and Porter (2011b).
[7] See Olsen and Porter (2010).

examines influencing factors and aims to identify which economic conditions promote the occurrence of Demand Surge effects in the aftermath of natural disasters.

The results should be beneficial for various market participants and should be the basis for a quantitative assessment of Demand Surge for future catastrophes. Among others, governments have to deal with rising economic damages and a deep understanding of Demand Surge is necessary to apply appropriate price regulations. Insurance companies are confronted with inflating claim levels and should consider Demand Surge effects with respect to premium calculation and determination of economic capital. Finally, building contractors should use this information for future capacity planning.

1.2 Course of Investigation

To analyze the research questions stated above this thesis is structured as follows. Fundamentals of catastrophe risk are discussed in Chapter 2. First, Section 2.1 provides definitions of the term disaster and aims at categorizing and defining costs of disasters. Next, the risk management chain of the International Graduate College 802 (IGC 802) is explained in detail in Section 2.2. This will be the frame of reference throughout this thesis and aims at defining a common standard for risk management discussion in an interdisciplinary context.

Chapter 3 deals with Demand Surge in general. First, general definitions are provided in Section 3.1. It is noteworthy that despite the importance of the Demand Surge effect no unique term or definition exist. Rather, each involved market participant has his own wording and understanding of this phenomenon. Section 3.2 provides an overview of events that are known to have produced Demand Surge in the past, before an overview of the regulatory framework is provided in Section 3.3. This section describes the coverage of Demand Surge by standard insurance contracts in the United States and Germany. Next, Section 3.4 deals with the impact of Demand Surge on labor and material prices. To this end, some theoretical considerations and examples are provided regarding the reaction of labor and material prices to the occurrence of natural disasters. The following

Section 3.5 gives an overview of the current state of the art in Demand Surge modeling. At the beginning, commercial Demand Surge models developed by the leading catastrophe modeling companies in the world are presented. Unfortunately, all model providers withhold details as intellectual property. As a consequence, the modeling results remain partly opaque. In addition, public and scientific Demand Surge models are described. Finally, Section 3.6 introduces our measurement approach of Demand Surge. This will be our theoretical framework and starting point for the following Chapters 4 and 5.

The empirical analyses in Chapter 4 aim to determine possible influencing factors on the Demand Surge effect. This can be either catastrophe specific or macroeconomic variables. Moreover, an approach to quantify the Demand Surge effect in an empirical setting is presented. Therefore, two of the three research questions stated above are addressed in this chapter. The fundamentals are presented in Section 4.1. Based on common assertions of the literature hypotheses concerning influencing factors on Demand Surge are derived in Section 4.2. The empirical analyses are established in Section 4.3. First, the empirical approach to quantify Demand Surge effects is presented. Second, the formulated hypotheses are tested based on two different data sets containing detailed information regarding natural catastrophes in the United States. In this context, the data selection and corresponding summary statistics are presented, too. The main results of this chapter are subsumed in Section 4.4.

Chapter 5 build upon the empirical setting in the previous chapter but with a focus on the economic perspective. Again, the fundamentals and research question are presented in Section 5.1. Due to the slightly changed focus in this chapter Section 5.2 provides a review of the literature regarding the impact of exogenous shocks on local labor markets and the corresponding wage effect. Afterwards, Section 5.3 describes the influence of Demand Surge on several possibly affected market participants. A slightly adapted set of hypotheses is introduced in Section 5.4. Section 5.5 describes the empirical strategy and issues related to the data used in the upcoming analyses. The empirical analyses itself are content of Section 5.6. First, influencing factors on the occurrence of a significant Demand Surge effect are analyzed, i.e., economic conditions that promote Demand Surge effects are identified. Second, the subset of observations with significant Demand Surge effects is analyzed in detail. Finally, the key findings of this chapter are summarized in Section 5.7.

Chapter 6 summarizes the results of the preceding chapters and addresses still unsolved research questions in the context of Demand Surge modeling.

2 Fundamentals of Catastrophe Risk

2.1 Economics of Natural Disasters

When describing and analyzing the impact and consequences of natural and man-made disasters it is of crucial importance to define important terms often used in the press and the scientific literature to ensure an unique understanding of these terms. Against this background, the main challenge of this section is to answer the following two questions:

- What is a disaster?
- How can costs of disasters be categorized and defined?

Therefore, the first task will be to provide different definitions of the term disaster. Almost every provider of disaster data, inspecting authority, (re-)insurance company, and state has his own definition. Very general disasters are "low-frequency, high-severity" events that lead to a perturbation of the economic system. According to the International Disaster Database EM-DAT[8] a disaster is defined as an event that fulfill at least one of the following criteria: (1) ten or more people reportedly killed, (2) 100 or more people reportedly affected, (3) declaration of a state of emergency, or (4) call for international assistance.[9] In contrast, Swiss Re defined a disaster in 2013 as an event that exceeded one of the following thresholds based on the type of disaster given in Table 2.1.[10]

[8]EM-DAT: The OFDA/CRED International Disaster Database - www.emdat.be - Université Catholique de Louvain - Brussels - Belgium.
[9]See Scheuren et al. (2008, p. 2).
[10]See Swiss Re (2014, p. 2).

Table 2.1: Swiss Re Disaster Definition Criteria 2013.

Insured losses (threshold in million US-$)	
Maritime disasters	19.3
Aviation	38.6
Other losses	48
or Total economic losses (threshold in million US-$)	
	96
or Casualties	
Lost or missing lives	20
Injured	50
Homeless	2,000

An overview of the world's disaster databases and their corresponding disaster definition criteria is provided by the Global Risk Information Platform (GRIP).[11] This overview is a result of the collaboration between the Centre for Research on the Epidemiology of Disasters (CRED) and the Global Risk Identification Program (GRIP). The Global Risk Information Platform is hosted by the United Nations Development Programme (UNDP), and financially supported by the United States Agency for International Development (USAID).

Hallegatte and Przyluski (2010) propose a categorization and definition of the different types of cost of a disaster, and, hence, should answer the second question.[12] At first, direct and indirect losses have to be distinguished. **Direct losses** describe the immediate consequences of a disaster, like a hurricane or an earthquake. These losses can be subdivided into direct market losses and direct non-market losses. Direct market losses refer to losses of assets, e.g., damaged buildings and/or infrastructure, or losses of services. These direct losses can be estimated quite easily, as these goods and services are traded on markets, and, therefore, can be estimated as the reconstruction or replacement costs. In contrast, direct non-market losses include loss of lives, damage to the cultural heritage or the natural environment. For all these damages it is nearly impossible to quantify the

[11]See http://www.gripweb.org/gripweb.

[12]Alternative but mostly similar categorizations and definitions can be found in ECLAC (2003), Pelling et al. (2002), and Committee on Assessing the Costs of Natural Disasters, National Research Council (1999).

monetary damage, as these assets are not traded on markets. A recent example would be the impact of the explosion and sinking of the Deepwater Horizon oil rig to the ecosystem in the Gulf of Mexico in 2010. Finally, BP paid billions of USD but it is still questionable if such a damage has a fair price at all. **Indirect losses** refer to the consequences of disasters and not to their immediate impact. Disasters often lead to a disruption of water and electricity supplies, and, therefore, lead to business interruptions. As a consequence, output losses arise and lead to a reduction in the total value added. But also negative losses might occur, e.g., during the reconstruction boom following the disaster. When considering both direct and indirect losses one can observe non linearity in **total losses**, which are defined as the sum of direct and indirect losses.[13] Figure 2.1 shows the evolution of indirect losses as a function of direct losses. Once direct losses reach 220 billion US-$ indirect losses coincide with direct losses, and, therefore, total losses are twice as large as direct losses. Thus, Hallegatte (2008) suggests that direct losses are not a good measure of disaster consequences and are inappropriate for risk management purposes. In addition, Hallegatte et al. (2007) define a measure called "Economic Amplification Ratio" (EAR) which is defined as the ratio of total losses to direct losses. To conclude, it is always important to keep in mind who publishes a disaster report and with which purpose.

In recent decades the frequency and severity of natural and man-made disasters show a growing trend, as presented in Figures 2.2 and 2.3. Despite the occurrence of mega catastrophes like Hurricane Katrina in the United States or the Tohoku earthquake in Japan during the last years, even more destructive events are thinkable in the foreseeable future, at least if effective disaster mitigation efforts are omitted.[14] In addition, analytic simulations already underlie the fear that even more destructive catastrophes might occur in the future.[15] The main drivers of the increasing severity of natural disasters are the increase of population and accumulation of assets in disaster prone areas. For example, Kunreuther and Michel-Kerjan (2009) state that during the years 1970 to 2010 the population of the state Florida grew from 6.8 million to approximately 19.3 million, which means an increase of more than 180%.

[13]See Hallegatte (2008, p. 792).
[14]See Pielke (2005) and Pielke et al. (2008).
[15]See Banks (2004).

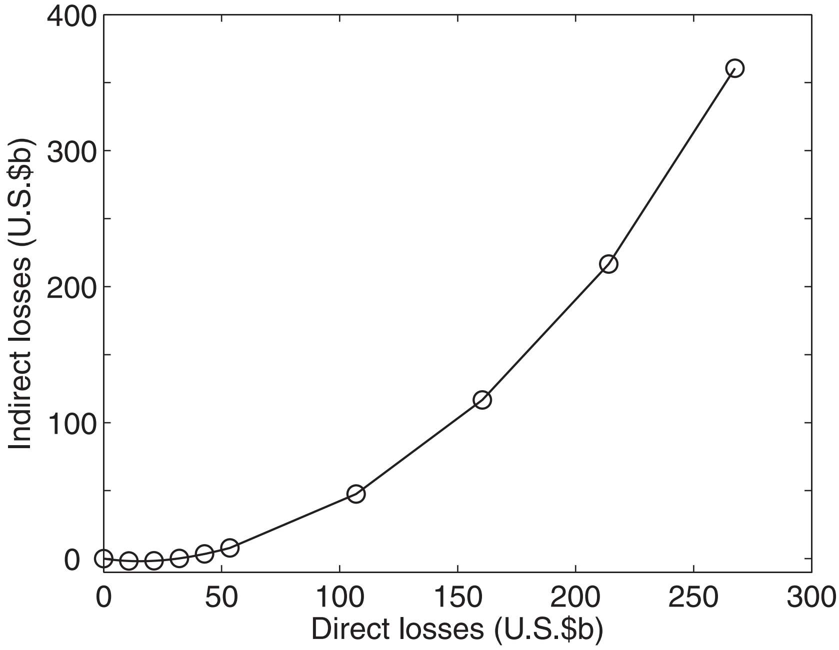

Figure 2.1: Indirect Losses as a Function of Direct Losses. Source: Hallegatte (2008).

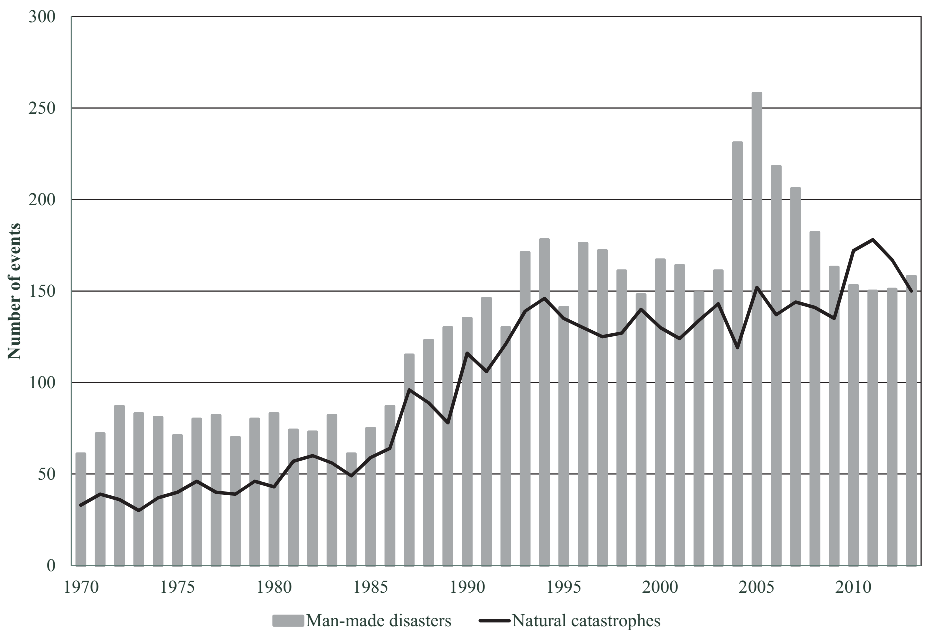

Figure 2.2: Number of Catastrophe Events 1970-2013. Source: Swiss Re (2014).

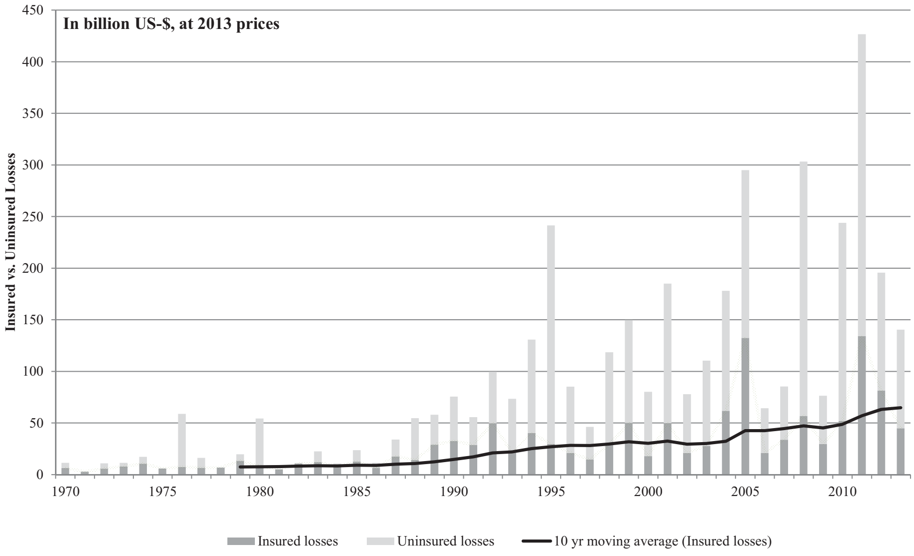

Figure 2.3: Insured vs. Uninsured Catastrophe Losses 1970-2013. Source: Swiss Re (2014).

Pielke et al. (2008) conducted a study in order to normalize hurricane damages in the United States for the time period 1900-2005. The original direct market losses were updated to 2005 using two different approaches. The first methodology was introduced by Pielke and Landsea (1998) and adjust for changes in inflation, wealth, and population. In contrast, the second approach was applied first by Collins and Lowe (2001) and adjust for changes in inflation, wealth, and housing units. Surprisingly, Katrina is not the costliest event ever. The Great Miami Hurricane in 1926 would result in direct market losses of 157 billion US-$ (Pielke/Landsea approach) or 139.5 billion US-$ (Collins/Lowe approach), much larger than the 81 billion US-$ in direct market losses of Hurricane Katrina. According to risk management theory protection against such mega catastrophes is most valuable.[16] Nevertheless, insurance claims regarding Hurricane Katrina only add up to 46.3 billion US-$ while the direct losses amount to 158.2 billion US-$ according to EM-DAT.[17] Figure 2.3 visualizes the discrepancy between insured and uninsured losses and it has to be noted that this under-insurance problem can even been observed in highly insured countries like the United States.[18] In addition, insurers themselves have to cope with rising insured losses. For example, the aggregate losses of Hurricanes Hugo (1989),

[16] See Froot (2001).
[17] Insurance claims data stem from Kunreuther and Pauly (2009, p. 2).
[18] See Cavallo and Noy (2010, p. 23).

Andrew (1992), Amber (1992), and Iniki (1992) caused the insolvency of 15 property and casualty insurers.[19] Against this background, the need for a holistic catastrophe risk management approach is obvious.

2.2 Catastrophe Risk Management

Within the International Graduate College 802 "Risk Management of Natural and Civilization Hazards on Buildings and Infrastructure" a probabilistic risk management chain was designed by Pliefke et al. (2007) to have a unique reference framework for all associated researchers.[20] Although each disaster type has different characteristics the handling within a risk management framework is quite similar. The general risk management chain consists of three major steps, which are risk identification, risk assessment, and risk treatment as presented in Figure 2.4.[21] During the first step potential risks to the predefined system under observation have to be identified. The following risk assessment step itself consists of the two procedures risk analysis and risk evaluation as can be seen in Figure 2.5. The main aim of the risk analysis is the quantification of risks. In this context two possible risk measures are provided. While the structural risk deals with structural damages to the system, the total risk assesses the corresponding losses.[22] The loss assessment includes both direct and indirect consequences and can be split up into economical, humanitarian, CSH (cultural, social, historical), and ecological aspects. The second procedure within the risk assessment phase is called risk evaluation and has the purpose to make different risks comparable to each other. Last but not least, public decision makers have to decide how to treat different risks to the system as part of the risk treatment phase. In a society with divergent objectives the target criteria should be to maximize the social welfare.

[19] See Banks (2004).

[20] For a more detailed description of the IGC 802 and the different research projects, see http://www.grk802.tu-braunschweig.de/grk_en.

[21] It is important to mention that the risk management chain of the IGC was developed mainly by civil engineers and has a strong focus on buildings and infrastructure.

[22] To this end, the authors provide the following two formulas: Structural Risk = Probability · Damage [Damage measure/year] and Total Risk = Probability · Loss [Loss unit/year]. See Pliefke et al. (2007, p. 7).

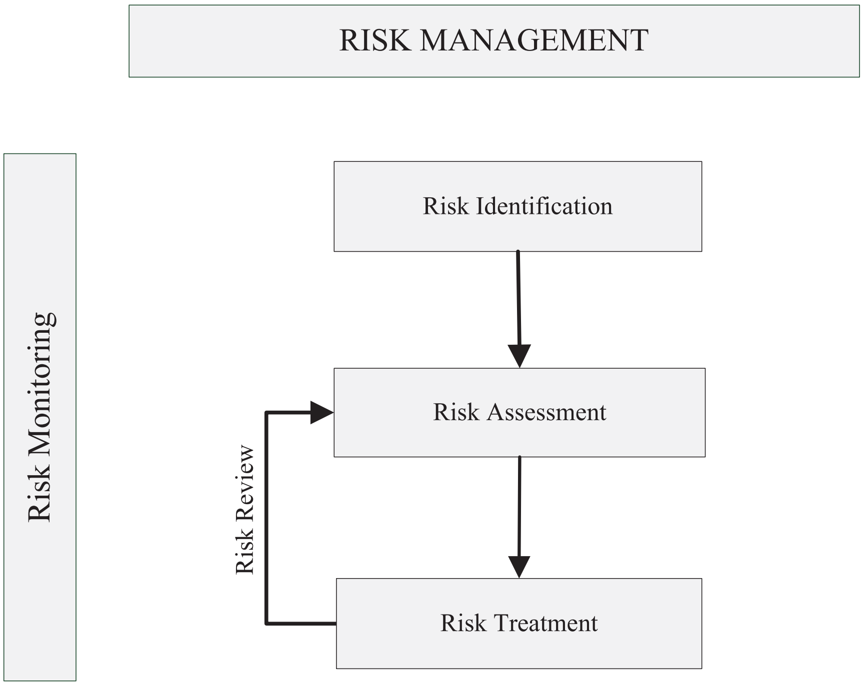

Figure 2.4: Risk Management Concept. Source: Pliefke et al. (2007).

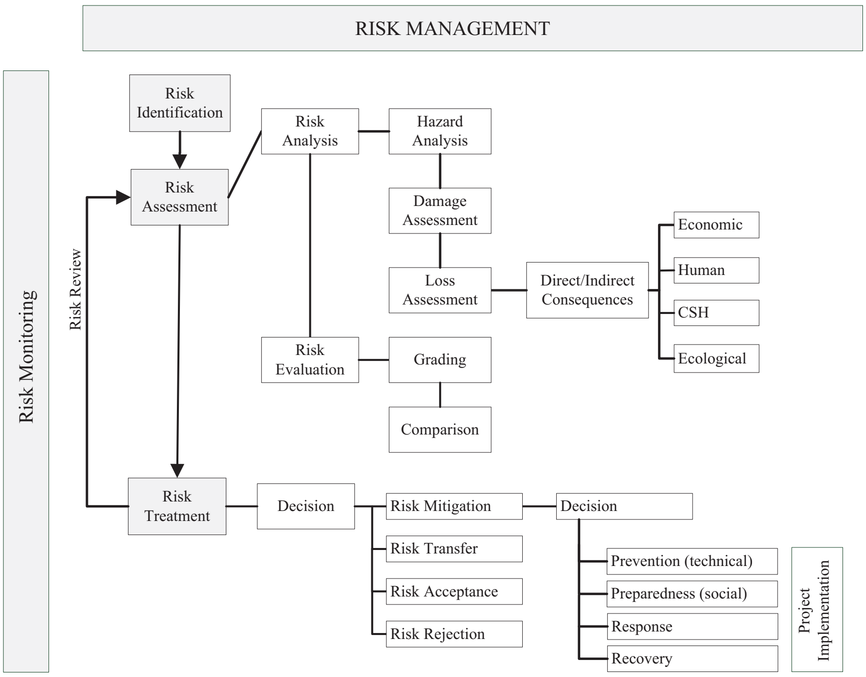

Figure 2.5: Risk Management Chain. Source: Pliefke et al. (2007).

The need for a globally accepted risk management standard and vocabulary was recognized by the International Standards Organisation (ISO) in 2009 as well.[23] The published ISO 31000:2009 and ISO Guide 73:2009 aim to provide risk management principles and guidelines for the public and to remove the still present ambiguity associated with concepts and definitions in risk management.[24] Therefore, the aim of the ISO 31000:2009/ISO Guide 73:2009 and the probabilistic risk management chain of the IGC 802 are quite similar. Both try to define a common standard for risk management discussion in an interdisciplinary context.

The present work tries to determine the economic consequences of natural and man-made disasters more accurate. To be more specific, the aim is to determine the impact of disasters on labor and material markets for reconstruction, and to derive a model which is able to identify relevant drivers of price increases in both markets. Based on this model parametrization even forecasts of future price evolutions are possible. Against this background, this work deals with direct and indirect consequences of disasters. On the one hand, price increases of reconstruction labor wages and materials are a result of the reconstruction boom in the disaster affected area, and, thus, an indirect consequence of the disaster. On the other hand, it is not appropriate to apply the wage and material price level under normal conditions to estimate direct market losses, i.e., to quantify the direct impact of the disaster in monetary units. Thus, the increased wage and material price levels have to be used to obtain an accurate estimate of the actual loss level. Of course, this increase does not solely depend on the total event impact, but also on the economic and political context. Thus, the implemented recovery activities by public authorities directly influence the price evolution as well. This is an excellent example for the implemented feedback system within the risk management chain. The risk review sub procedure (see Figure 2.5) implements all new information, knowledge, and experience into the risk management process, and, therefore, can be used to evaluate public policy actions.

[23]See International Standards Organisation (2009a) and International Standards Organisation (2009b).
[24]See Purdy (2010).

A deeper understanding of these price effects is relevant for various market participants. Hence, a brief explanation of the influence on some market participants and their potential consequences is provided next. In case of disasters, governments have to deal with rising total costs. In this context the consideration and the comprehension of rising reconstruction costs is relevant for governments to ensure adequate catastrophe precautions and appropriate price regulations in the construction sector. Such official regulatory procedures allow governments to directly manage the Demand Surge effect. Price regulations are, e.g., conceivable to restrict price increases after a catastrophe but might also lead to a longer reconstruction period because fewer workers from other regions can be attracted. However, such regulations are only reasonable if the government understands the influence of reconstruction price increases on the social welfare. Indeed, it is not immediately clear if the price increase has a negative effect on the social welfare because higher prices imply higher supply and consequently a faster remedying of damage and a decrease in underproduction.[25] While governments are confronted with increasing total losses, insurance companies have to deal with inflating claim levels due to rising reconstruction costs for insured and damaged properties. Therefore, insurance companies have to consider price increases for the calculation of insurance premiums and the determination of economic capital[26]. With respect to the determination of economic capital it should be noted that, particularly if tail events (like great catastrophes) occur, considering or not considering price increases in the reconstruction sector can be the difference between insolvency and solvency for an insurance company. To provide some anecdotal evidence, Munich Re recommends a Demand Surge effect in the range of 30%–40% in matters of Hurricane Katrina.[27] Unfortunately, insurance companies in part disregard these effects in current loss models.[28] Building companies should have great interest in Demand Surge modeling because they have to estimate future demand which in turn depends on the price level to plan future capacities and profits in situations of catastrophe-induced reconstruction. Especially regarding recruitments a detailed knowl-

[25]See Hallegatte et al. (2008) and Hallegatte (2008).
[26]The economic capital is defined as the amount of capital that is needed to cover the losses of a financial institution with a predefined confidence level. See Elizalde and Repullo (2007).
[27]See Munich Re (2006b, p. 5).
[28]See Munich Re (2006a, p. 14).

edge of the duration of the Demand Surge effect is of crucial importance. For investors of insurance companies estimates of increasing reconstruction costs are also highly relevant to assess the price reactions of insurance stocks after catastrophes. While claims payments reduce the market value, potential new premium income, due to an increasing risk sensitiveness of the population, has the opposite effect. Ex ante it is hard to distinguish which of these two effects is predominant.[29] Finally, issuers and investors of catastrophe-linked securities have to determine the risk profile of catastrophe losses and the price reaction of these securities due to the occurrence of natural and man-made disasters. Particularly for Cat Bonds[30] with implemented indemnity trigger[31] the payoff depends on the actual losses due to the catastrophe, so that Demand Surge effects are relevant for investors of these securities.

Thus, price effects in the market for reconstruction labor and material should be considered in a holistic risk management approach in matters of disasters. Hence, the next chapter will summarize the current state of knowledge regarding disaster induced price effects in the reconstruction sector.

[29] See Gangopadhyay et al. (2010), Lamb (1995), Marlett et al. (2000), and Shelor et al. (1992).

[30] A Cat Bond is a financial instrument that is used to transfer a specified catastrophe risk from a sponsor, usually a (re-)insurer, to investors. In so doing Cat Bonds transfer catastrophe risk from reinsurance markets to financial markets. See Galeotti et al. (2013).

[31] With respect to Cat Bonds different trigger types can be implemented which are in particular indemnity-, index-, and hybrid triggers. In case an indemnity trigger is implemented the sponsor of the Cat Bond transaction is indemnified as if he had purchased catastrophe reinsurance. See Cummins (2008).

3 Demand Surge

In this chapter general definitions of Demand Surge are provided in Section 3.1 initially. Second, some anecdotal evidence of disasters that are known to have or have not produced Demand Surge in the past is presented in Section 3.2. To give an overview of the regulatory framework the current legal situation in Germany and the United States concerning price increases of damaged and insured assets is content of Section 3.3. In this context, especially the liability of insurers will be discussed in detail. As both price increases in building materials and services are thinkable during a reconstruction boom following a disaster, Section 3.4 discusses differences between both markets and the corresponding price evolution. In the following Section 3.5 different Demand Surge models will be described in detail. The chapter concludes with the description of a novel approach to measure Demand Surge effects in Section 3.6.

3.1 General Definitions

Generally speaking, Demand Surge describes any demand induced inflation in reconstruction costs after the occurrence of a huge natural disaster, like Hurricane Katrina in 2005 or the 1994 Northridge earthquake. Although Demand Surge is not a new phenomenon, not limited to one region or country, and not unique to one or two perils, there is more or less no common body of knowledge or standard definition. Moreover, the economic mechanisms that underlie Demand Surge are usually similar, despite the fact that the consequences and circumstances of each disaster are unique and depend heavily on the vulnerability of the region and their inhabitants. Against this background, Olsen and

Porter (2011a) give an overview of different definitions of Demand Surge. Based on a review of the literature four types of definitions were identified.[32]

1. Demand Surge describes the temporary increase in local reconstruction costs, which is induced by increasing labor wages, material prices, and other specific costs. In this context specific costs might be overpayment of claims by insurers or special repairs that are necessary to comply with new or updated building codes.

2. Some definitions just focus on labor wages and material prices, excluding other specific costs mentioned in the first definition.

3. Demand Surge is an increase in reconstruction costs following a huge natural disaster, meaning that the repair costs for a single house are ceteris paribus higher after a disaster compared to a situation that only a single house is damaged. With respect to possible explanations no details are provided.

4. Demand Surge is the difference between actual and expected (or modeled) monetary losses.

In our upcoming empirical analyses in Chapters 4 and 5 we will focus only on labor wages/labor costs and will neglect all other possible reasons for Demand Surge effects mentioned above. For example, a consideration of specific costs mentioned in the first definition of Demand Surge is problematic because such data are not readily available. A discussion of the impact of natural disasters on labor and material prices is provided in Section 3.4.

3.2 Historical Evidence

A comprehensive overview and discussion of historical events that are known to have or have not produced Demand Surge is provided by Olsen and Porter (2010). Due to their

[32] A detailed timeline regarding the use of the term Demand Surge by different market participants (commercial catastrophe modelers, insurers, media, ...) is provided in Olsen and Porter (2010). Starting in 1975 definitions and examples are classified according to the following scheme.

findings Demand Surge is not a new phenomenon. First evidence can already be found in the 18th-century England. Moreover, Demand Surge can in principle occur in any region of the world. For example, past events that are known to have produced Demand Surge were located in the United States, the United Kingdom, Australia, and Central Europe. In addition, Demand Surge is not restricted to a particular type of catastrophe. Amongst others, observations of Demand Surge are available for hurricanes, earthquakes, floods, and wildfires.[33]

At this point, we do not aim to provide an exhaustive documentation of past events and the circumstances that led or led not to the occurrence of Demand Surge. Rather, we will focus on some selected past events to highlight the variety of observations and refer to Olsen and Porter (2010) for a more detailed description and discussion. First evidence of Demand Surge is already provided by Defoe (1704) for the Great Storm of 1703, that destroyed a huge part of roofs in Southern and Central England in November 1703. Olsen and Porter (2010) citing Defoe (1704) report significant increases for reconstruction material and labor that were caused by a strong imbalance between demand and supply. Although scarce resources were substituted by alternative materials, prices for single resources, like plain tiles, rose by up to 470%. In contrast, the 1886 Charleston, South Carolina earthquake occurred in the United States and provide documented evidence for increasing wages for bricklayers and plasterers of up to 170%. In this case, the excess demand was so strong that hundreds of applications from laborers all over the United States were received, which were attracted by the high wage level in Charleston. Cyclone Tracy in 1974 provides evidence for another continent suffering from Demand Surge. Tracy destroyed the isolated town of Darwin in Australia and led to significant reconstruction cost increases. Altogether, two main reasons for the cost increases could be identified in this case. On the one hand, the remote location of Darwin made it difficult to import labor and materials. On the other hand, higher adopted building standards led to an additional upward pressure on reconstruction costs. Finally, there is also evidence for some catastrophes which are unknown to have produced Demand Surge. Examples include the 1989 Hurricane Hugo and the 1989 Loma Prieta earthquake in the United

[33] See Olsen and Porter (2011b).

States. A possible explanation with respect to the Loma Prieta earthquake is that it did not hit a major urban area.[34]

But also in recent decades there is evidence for Demand Surge effects. Auguste Boissonnade, vice president of product development Risk Management Solutions (RMS), said in an interview that average reconstruction labor costs increased by about 15% in the aftermath of Hurricane Katrina in Louisiana in 2005. This effect was even more pronounced in coastal counties. In addition, Boissonnade emphasized that maximum price increases of 20% to 50% are possible when labor cost changes are computed on a quarterly basis.[35] Similar results are provided by the commercial catastrophe modeling companies. Applied Insurance Research (AIR), EQECAT, and RMS estimated Demand Surge effects in the range of 10% to 40% after Katrina.[36] In addition to this findings, Mendell (2006) stresses that price impacts on building materials following Hurricane Katrina were short-term,[37] whereas the impact on building services in the medium to long-term is unclear. As another example, Kuzak and Larsen (2005) state that in the aftermath of the 1994 Northridge earthquake claims settlement costs rose by up to 20%. In addition to the US market, Demand Surge effects could be observed for Australia, too. For example, the Australian Securities & Investments Commission conducted a survey after Cyclone Larry in March 2006 and estimated that building costs increased by at least 50%.[38] In addition, Olsen and Porter (2011b) citing Sweetman and Morris (1999) report a tremendous 2,000% increase in the service to fix a tarpaulin to a damaged roof after the 1999 Sydney hailstorm.

[34] See Olsen and Porter (2010).
[35] See Zeman (2009).
[36] See Guy Carpenter (2005).
[37] Hurricane Katrina did not affect the production potential and capacity in the first place but more the ability to supply the catastrophe affected regions with necessary building materials.
[38] See Australian Securities & Investments Commission (2007).

3.3 Regulatory Framework

The Actuarial Standards Board (2000) defines Demand Surge as a "sudden and usually temporary increase in the costs of materials, services, and labor due to the increased demand for them following a catastrophe". In this context, a catastrophe is defined as a low-frequency, high-severity event. The additional costs due to Demand Surge effects are directly passed on to the insurer (and the consumer).[39] Extended replacement cost coverages, for example, cover price increases up to a predefined amount.[40]

Similar regulations can be found in Germany for residential properties. The Gesamtverband der Deutschen Versicherungswirtschaft (GDV) e.V. (2011) provides general terms and conditions and specifies inter alia types of natural disasters that are covered by insurance contracts. One of these conditions (§8) deals with additional costs resulting from price increases after the occurrence of insured events and emphasize that additional costs up to a predefined level have to be paid by insurance companies. Therefore, individual households and homeowners are protected from Demand Surge effects up to an ex ante specified amount.

Moreover, the European Insurance and Occupational Pensions Authority (EIOPA) stresses in its recent stress test the importance of Demand Surge. Participating insurers are requested to consider Demand Surge effects when using catastrophe models to determine their exposure.[41]

3.4 Impact on Labor and Material Prices

According to the definitions of Demand Surge in Section 3.1, increases in labor and material prices could be relevant for the occurrence of Demand Surge effects and lead to higher reconstruction costs. However, consecutively we will present objective reasons

[39] See EQECAT (2005).
[40] See Danise (2013).
[41] See European Insurance and Occupational Pensions Authority (2014).

and historical time series data that lead to the conclusion that labor prices should be the center of attention. In general, labor is relatively immobile, and its markets tend to be strongly regional. In case of a catastrophe, labor demand increases sharply and exceeds regional capacities. As a consequence, workers are stimulated to work overtime, which is associated with a premium. Moreover, the import of labor is associated with extra costs for accommodations and travel. On the contrary, building materials are traded on global markets and can be transported to devastated areas more easily. Thus, the regional imbalance between demand and supply is less distinct, making prices for building products less volatile. Moreover, states that are frequently affected by catastrophe events often try to conduct agreements with large chain stores, such as Walmart, that offer them access to building products typically used for reconstruction purposes at predefined conditions.[42] As a consequence, the excess demand and the impact on material prices are less pronounced. Nevertheless, exceptions are possible. For example, regional cement prices rose significantly after the landfall of Katrina because cement was imported mainly through the harbor of New Orleans, which had a bounded capacity during that time.[43]

In addition, we present example labor and material price evolutions in Figures 3.1 and 3.2 that underpin our theoretical reasons. Figure 3.1 shows labor price evolutions in West Palm Beach (Florida), Florida, and the United States (US) from 2002 to 2009, which include the landfall of Hurricane Frances in West Palm Beach (Florida) in Q3 2004. Figure 3.2 plots the respective material price evolution. Whereas a sharp increase in labor prices coincides with the landfall of Frances, the material prices react little, pointing again to the fact that labor prices should be the center of attention.

In summary, labor capacity seems to be the restrictive factor. As a consequence, the demand for building materials is distributed over a longer time period. Moreover, this additional demand is predictable to some extent. Thus, the production capacity can be adapted to the change in demand, and the impact on material prices is less pronounced. This finding is supported by work conducted by Olsen and Porter (2011a) and AIR Worldwide Corporation (2009a). Olsen and Porter (2011a) show that correlation between

[42]Personal communication with Prof. Randy E. Dumm, August 6, 2013.
[43]See Hallegatte et al. (2008, p. 19).

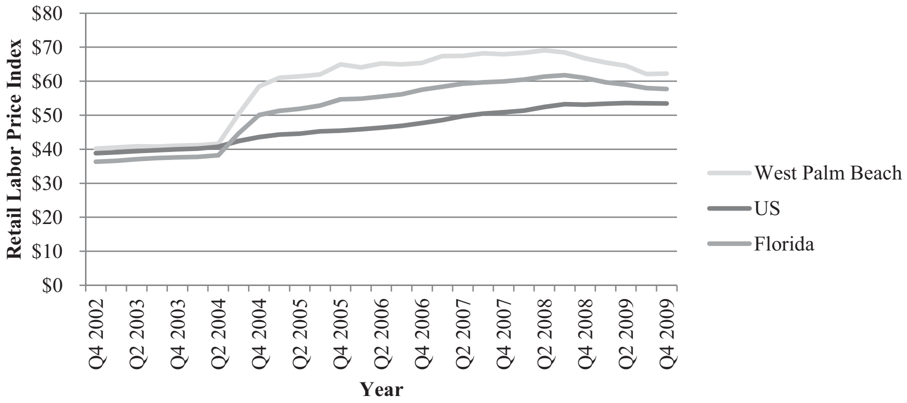

Figure 3.1: Retail Labor Price Index.

The figure shows the price evolution of the retail labor price index for West Palm Beach (Florida), Florida, and the entire US from Q4 2002 to Q4 2009.

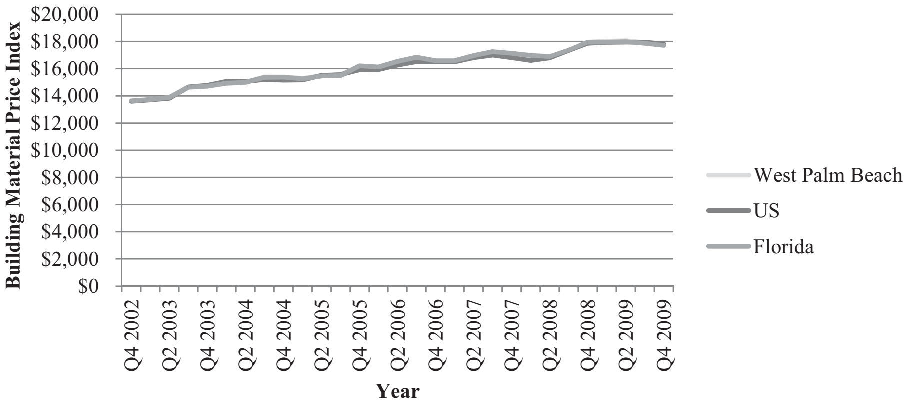

Figure 3.2: Building Material Price Index.

The figure shows the price evolution of the building material price index for West Palm Beach (Florida), Florida, and the entire US from Q4 2002 to Q4 2009.

surface wind speed, as a proxy for damage, and material prices is low. This relationship is visualized with the help of a scatterplot in Figure 3.3. Cost changes of residential and commercial baskets of building materials from July to January seem not to be influenced by surface wind speed of proximate storms during the Atlantic hurricane season. In contrast, the respective baskets for labor components show a positive relationship between cost changes and surface wind speed. Notably is the finding that more or less all extreme market cost changes relate to observations in Florida in 2004.

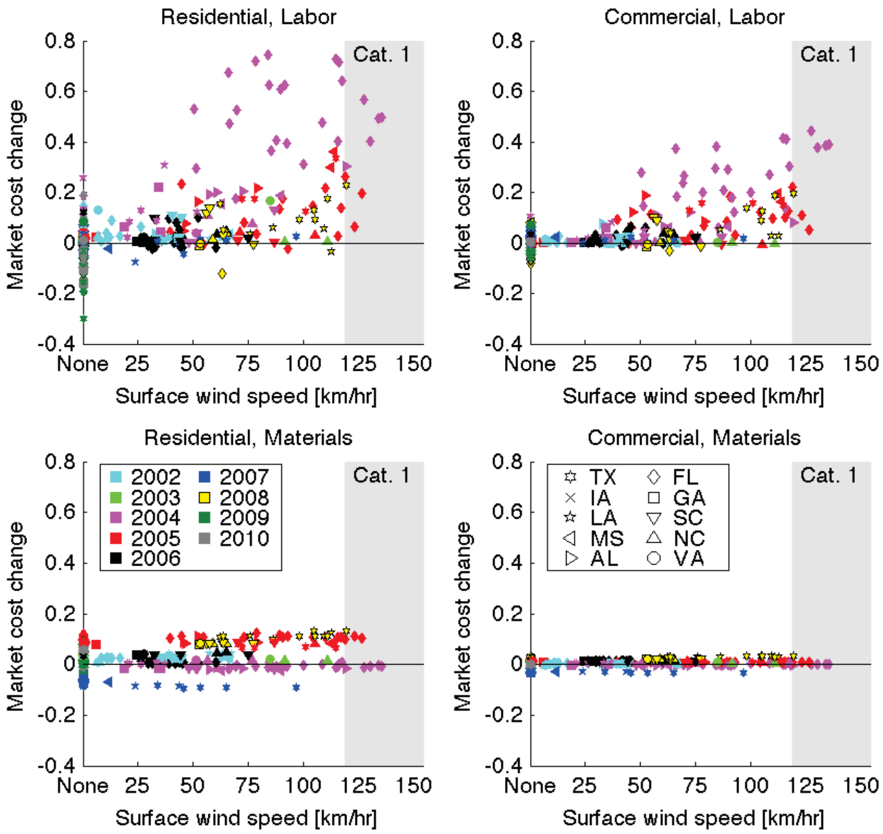

Figure 3.3: Cost Changes of Constructed Baskets of Repairs vs. Wind Speed. Source: Olsen and Porter (2011a).

The figures show the actual price evolutions of constructed baskets of repairs both for residential and commercial properties versus surface wind speed of a proximate storm. The symbol colors represent different Atlantic hurricane seasons, whereas symbol shapes represent different states. Accordingly, the abbreviations of states are defined as follows: TX (Texas), FL (Florida), IA (Iowa), GA (Georgia), LA (Louisiana), SC (South Carolina), MS (Mississippi), NC (North Carolina), AL (Alabama), and VA (Virginia).

3.5 Demand Surge Models in Theory and Practice

Only two decades ago, researchers started to develop models to describe Demand Surge.[44] Based on the issuer of the model, three categories can be build: commercial, public, and scientific catastrophe models. Leading among them are models developed by the three main catastrophe modeling companies: AIR, EQECAT, and RMS. All three steadily improve their models but withhold most details as intellectual property. As a second cat-

[44]See Olsen and Porter (2010, p. 24).

egory, public catastrophe models implement Demand Surge modules in their loss models. In addition, just a few scientific articles exist, dealing with varying aspects of Demand Surge. Against this background, a comprehensive overview of different Demand Surge models is presented next.

3.5.1 Commercial Models

3.5.1.1 AIR

The AIR Demand Surge function is briefly described in AIR Worldwide Corporation (2009a) and was first introduced in 1992.[45] The Demand Surge function is calibrated on the basis of just a few historical catastrophes in the US, and, therefore, the results are only specific to the US. In agreement with the results of Section 3.4 AIR identifies increased labor costs as the driving force of observable Demand Surge effects.

The Demand Surge component of a catastrophe model usually modifies the calculated ground-up loss[46] of a given insurance portfolio. To this end, a Demand Surge factor is calculated. This factor varies generally between 1.0 and 1.6 and is multiplied by the ground-up loss.[47] In case of AIR the implemented Demand Surge factor is a function of the insurable industry loss, and triggered at an insurable industry loss of 5 billion US-$ in the 48 contiguous states and 2 billion US-$ in Alaska and Hawaii. A qualitative impression of this functional relationship is given in Figure 3.4. In addition, the Demand Surge function varies by type of coverage. AIR Worldwide Corporation (2009a) distinguishes between structures and appurtenant structures (coverages A and B), contents (coverage C), and time element losses (coverage D, including additional living expenses and business interruption losses).

An overview of calculated Demand Surge factors of past catastrophes regarding coverages A and B can be found in Table 3.1.

[45] A sample Demand Surge validation regarding Hurricane Frances is provided in the contained appendix.
[46] The ground-up loss of a property is the monetary cost to repair the damages. Deductibles, limits, and

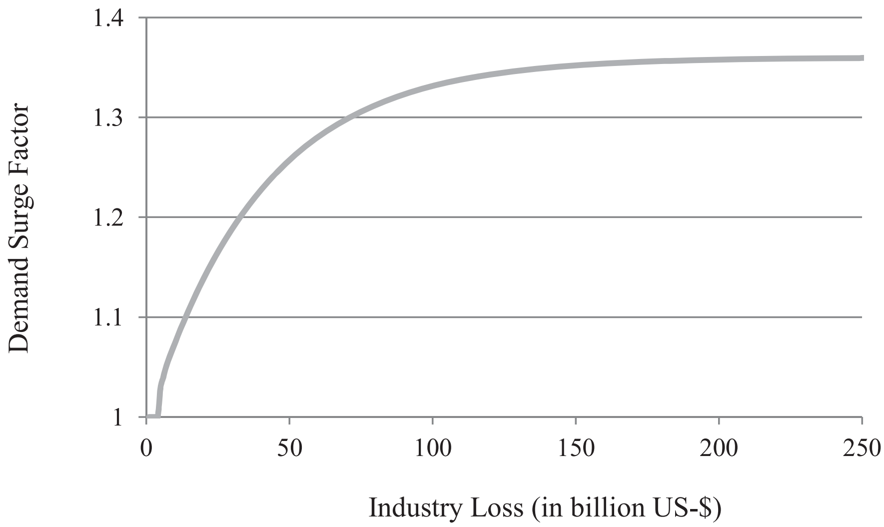

Figure 3.4: AIR Demand Surge Function. Source: AIR Worldwide Corporation (2009a).

The figure shows the functional relationship between the Demand Surge factor and the insurable industry loss for all types of coverages combined.

Table 3.1: Demand Surge Factors by Events.

Source: AIR Worldwide Corporation (2009a).

Event	Demand Surge Factor
Charley	1.19
Frances	1.16
Ivan	1.12
Jeanne	1.19
Katrina	1.07
Rita	1.09
Wilma	1.08

Besides that, AIR Worldwide Corporation (2009b) discusses the impact of the overall economy on Demand Surge, and concludes that during recession periods the Demand Surge function shown in Figure 3.4 may be shifted to the right due to additional available capacities in local labor markets.

co-pays are not considered. See Born and Martin (2006).
[47]See Olsen and Porter (2011b).

3.5.1.2 EQECAT

A brief description of an early model developed by EQECAT can be found in Olsen and Porter (2011b) and Olsen and Porter (2010). Due to the fact that EQECAT withholds details as intellectual property the only available information regarding the implemented Demand Surge model goes back to the mid-1990s. At that time EQECAT identified possible influencing factors on Demand Surge. These are mainly the following: price gouging for building materials, services, and equipment; delayed repairs; substitution of materials and union labor due to limited supply; greater effort to conduct repairs because of limited accessibility of the catastrophe region and the need to import labor, materials, and equipment from outside.[48] Based on these findings, EQECAT created an empirical Demand Surge model for hurricanes in the United States that differs with respect to residential and commercial claims.

The resulting functional relationship of the model looks like this:

$$L = \sum_i C_i \cdot y_i(e_i) \cdot [1 + P(e_i) \cdot DS(T)], \tag{3.1}$$

with:

- L = ground-up loss of a given portfolio;
- i = individual property within the portfolio;
- C = estimated replacement cost;
- e = intensity of environmental excitation (wind speed, flood depth, ...);
- $y(\cdot)$ = mean damage factor[49] as a function of e;
- $P(\cdot)$ = maximum effect of Demand Surge as a function of e;
- T = total repair costs as a fraction of annual construction revenues;
- $DS(\cdot)$ = Demand Surge effect of the event as a function of T.

[48] See Olsen and Porter (2010).
[49] A damage factor quantifies the repair costs as a fraction of replacement cost. It is noteworthy to state that some authors use the term damage ratio instead of damage factor to avoid confusion.

According to Olsen and Porter (2011b) the function $P(\cdot)$ might have the co-domain $[0, 0.6]$ for property classes whose maximum Demand Surge is known to reach 60%. $P(\cdot)$ reaches its maximum value at intermediate levels of excitation and is 0 at low and high excitations. The underlying assumption behind this approach is that at both low and high levels of excitation repairs can wait as damages are either negligible or so severe that it makes no difference to hurry up or not. Thus, prices will have fallen until repairs will start and Demand Surge is 0. This effect is specific to each property. In contrast, $DS(\cdot)$ captures the potential Demand Surge effect of an event as a whole, e.g., the potential Demand Surge effect of an earthquake in the metropolitan area of San Francisco. $DS(\cdot)$ is restricted to the interval $[0, 1]$ depending on the realized value of T. T in turn is defined as the ratio of the estimated total repair cost to the estimated annual construction revenues of building companies located within a given radius of the event location. In general, this radius is set to 480 km, whereas the radius is reduced to 160 km for locations with only one major interstate connection. As Hurricane Hugo in 1989 is assumed to have not caused Demand Surge effects, DS is set to 0 if the calculated ratio is less than the one calculated for Hurricane Hugo. In contrast, Demand Surge is set to 1 if the ratio reaches or exceeds the one estimated for Hurricane Andrew in 1992.

Of course, this is just a brief description of an early Demand Surge model but, nevertheless, some insights into underlying drivers of Demand Surge are provided. First, the relation of demand and supply in the local construction sector is of crucial importance and captured through T in the model. Moreover, the location of a catastrophe matters. If a region is readily accessible, workers from surrounding regions can more easily attracted to help to restore the original state of buildings and infrastructure. This effect is included in the calculation of T through the choice of different radii for the definition of the potential labor supply. Finally, repair delays are only important at mean levels of excitation when speed of reconstruction is of crucial importance. This was the reason for the maximum of $P(\cdot)$ at intermediate levels.[50]

[50]See Olsen and Porter (2011b).

3.5.1.3 RMS

In line with the disclosure policy of AIR and EQECAT only some hints regarding the developed Demand Surge model by RMS can be found.[51] RMS uses the term post catastrophe loss amplification (PLA) to refer to the increase in costs of an original damage when this damage is part of a major catastrophe. The main drivers of PLA according to RMS are:

- **economic Demand Surge**:
  Economic Demand Surge describes the increase in repair costs as a result of an excess demand in the markets for reconstruction labor and materials. The causes can be classified into direct, indirect, and exogenous ones. The direct cause is the unexpected increase in demand for reconstruction labor and material that overwhelms the local construction capacity. Indirect causes can be the local labor force reduction as a consequence of evacuations, impairments due to damages to facilities, or the reduced accessibility of catastrophe regions. Finally, exogenous causes are the available capacity of the construction sector prior to the catastrophe, and global pressure on material prices in the preceding months. A sketch of the calculation of economic Demand Surge is provided in Figure 3.5.
- **deterioration vulnerability**:
  If repairs are delayed, damage repair costs will increase due to time dependent damage escalation. For example, after the massive destruction of the city of New Orleans by Hurricane Katrina in 2005 the main task was to reconstruct a whole city instead of just a few districts as usual. Consequently, reconstruction could start only after the city urban planning was finished. Another source of delay in this case were legal issues arising due to the fact that buildings were affected both by wind and storm surge.[52]
- **claims inflation**:
  Insurers might decide to relax their procedures to settle claims to circumvent insurance fraud and exaggerations by claimants. To provide some anecdotal evidence,

[51] See Souch (2010) and Boissonnade et al. (2007).
[52] See Hallegatte et al. (2008).

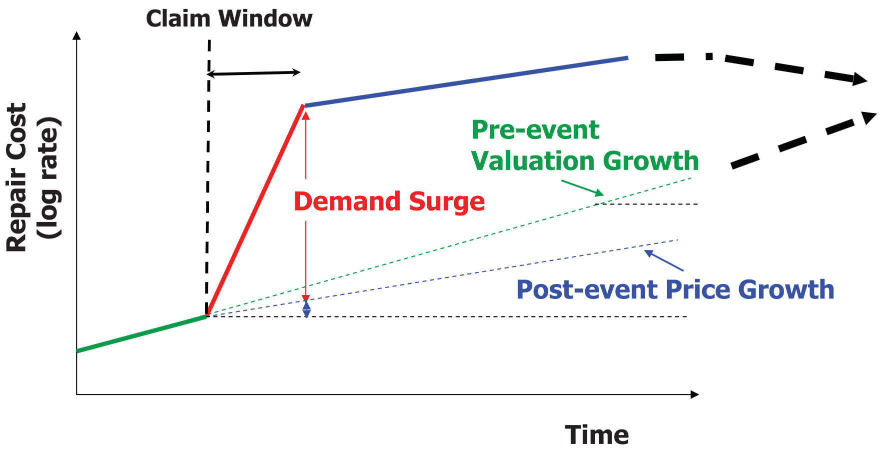

Figure 3.5: Demand Surge Calculation. Source: Boissonnade et al. (2007).

The figure shows the quantification of the economic Demand Surge effect. For a given claim window Demand Surge is defined as the gap between the actual price evolution of repair cost and the price growth in the event no catastrophe had occurred.

a study conducted after the 1999 Windstorm Anatol in Denmark by associations of the Nordic countries claims that approximately 10% of total insurance payouts were due to insurance fraud.[53]

- **coverage expansion**:
  Insurers might expand their insurance terms and coverages as a result of pressure from politics and media. As a consequence, the insurance ratio, i.e., the ratio of insured damages to total damages, rises and the reconstruction demand is more heavily concentrated. Even if some part of the uninsured damage might be repaired, this reconstruction activity is generally distributed over a longer time period, and, therefore, smooths the overall reconstruction demand. For example, the government of France forced insurers to reduce deductibles after the 1999 Windstorms Lothar and Martin in France.[54]

Before the occurrence of Hurricane Katrina in 2005 RMS's catastrophe models only considered economic Demand Surge. The possibility of a mega catastrophe affecting major urban and economic areas, like New Orleans, was the starting point for the im-

[53]See Souch (2010).
[54]See Boissonnade et al. (2007).

plementation of a broader PLA component, which was launched in 2006. Especially the extraordinary high loss amplification in the aftermath of the 2004 and 2005 hurricane seasons was not captured by economic Demand Surge.

Against this background, RMS declares that insurers are generally captured between two mutually exclusive goals. On the one hand, insurers would like to postpone repairs until prices have fallen in order to minimize insurance claims payouts. On the other hand, they are concerned about their level of customer satisfaction. As a consequence, insurers will have to find a middle ground based on results of PLA assessments.[55]

3.5.1.4 Risk Frontiers

Risk Frontiers was founded in 1994 as an independent research center with the aim to provide its sponsors with detailed information regarding natural hazard risks in the Asia-Pacific region. All its sponsoring companies are working in the insurance industry, like, e.g., Swiss Re, Aon Benfield, or Guy Carpenter. McAneney (2007) discusses factors contributing to post-event claims inflation (PECI), which is defined as an inflation in insurance claims payouts following a catastrophe. One component contributing to PECI is Demand Surge. Other components of PECI include, but are not limited to, fraud, response of the government, and the magnitude of the catastrophe. Based on different ranges of total market losses Risk Frontiers assigns one PECI factor to each predefined loss range. This PECI factor in turn should be multiplied with the estimated company loss. As McAneney (2007) contains only interim results the concrete shape of PECI, nevertheless, remains opaque.

[55] See Souch (2010).

3.5.2 Public Model

Regarding public catastrophe models incorporating Demand Surge modules, only the Florida Public Hurricane Loss Model (FPHLM)[56] is known so far.

3.5.2.1 Florida Public Hurricane Loss Model

The FPHLM is funded by the Florida Office of Insurance Regulation. The model is restricted to hurricane events in Florida, and estimates costs and probable maximum loss levels. All estimates therein refer to personal lines residential property. The incorporated Demand Surge module is affected by insurance coverage, the region of Florida, and estimated statewide losses before applying the Demand Surge function.

Regarding the affected region of Florida the authors differentiate between the following regions:

- Northeast / North Central,
- Northwest,
- Central,
- South (except Monroe County),
- Monroe County.

Different Demand Surge factors are defined depending on the type of coverage. This procedure is quite similar to the one applied by AIR (see Section 3.5.1.1). Of crucial importance is the definition for structures, as all other Demand Surge factors regarding appurtenant structures, contents, and additional living expenses (ALE) are related to the Demand Surge factor for structures.

[56] See Florida International University (2009).

Based on estimated statewide losses before applying Demand Surge effects, the following functional relationship between Demand Surge and statewide losses is defined:

Structures:

$$Demand\ Surge\ factor = c + p_1 \cdot ln\,(statewide\ losses) + p_2, \tag{3.2}$$

where c is a constant, p_1 is a parameter unique to all regions except Monroe County, and p_2 is an additional parameter that varies by affected region. Based on equation 3.2, Demand Surge factors for all remaining types of coverages are defined as follows:

Appurtenant Structures:

$$Demand\ Surge\ factor = Structure\ factor; \tag{3.3}$$

Contents:

$$Demand\ Surge\ factor = 0.3 \cdot (Structure\ factor - 1) + 1; \tag{3.4}$$

ALE:

$$Demand\ Surge\ factor = 1.5 \cdot Structure\ factor - 0.5. \tag{3.5}$$

To gain a deeper understanding of the proposed Demand Surge factors for different types of coverage, the development of the Demand Surge factor for structures will be explained in detail. Based on a construction cost index provided by Marshall & Swift/Boeckh, indices for all five geographic regions specified above were produced. For ten historical storm/region combinations a historical Demand Surge factor was calculated. To this end, the authors projected the observed construction cost index in each affected region and compared this hypothetical index level with the actual evolution. Each potential gap between the actual and hypothetical index level was assumed to be triggered by Demand Surge effects. This approach is very similar to the one applied by RMS for the determination of economic Demand Surge effects. Finally, these results were generalized to obtain the functional relationship for the Structure factor defined in equation 3.2. As Monroe County was not affected by a major disaster during the calibration period of the Demand Surge functions above, parameters were assigned judgmentally. The limited access of Monroe County was the main reason for even higher assigned parameter values p_1 and p_2 in equation 3.2 compared to the remainder of South Florida. In a catastrophe scenario it is reasonable to assume that the Overseas Highway will be blocked, which would make the supply of the Keys with required building materials and services more challenging than for the rest of Florida.

Since there is no objective reason why the Demand Surge factor should differ between structures and appurtenant structures both are assigned the same value. The rationale behind the determination of the contents Demand Surge function was to relate any catastrophe induced consumer price increase to the structure Demand Surge factor. With respect to the occurrence of hurricanes Katrina and Wilma in Southeast Florida the increase in consumer prices was approximately 30% of the identified increase in reconstruction costs. Hence, this percentage was chosen to quantify the relationship between the structure and contents Demand Surge factor. The definition of the ALE Demand Surge is based on the Structure factor, too. Generally, higher structure Demand Surge factors result from a more pronounced disequilibrium between demand and supply in the market for reconstruction labor and material. This mismatch in turn leads on average to longer reconstruction periods, and, therefore, increasing ALE.

3.5.3 Scientific Models

So far, only two scientific publications exist that focus directly on the quantification of Demand Surge. Hallegatte et al. (2008) conduct an analysis of increasing reconstruction costs in the aftermath of the 2004 and 2005 hurricane seasons in Florida. By contrast, Olsen and Porter (2011a) use a series of multilevel regressions to predict the cost changes of constructed baskets of repairs representing the total repair costs, material, and labor components caused by Atlantic hurricanes. The model is based on data for nine hurricane seasons and 52 cities on the Atlantic and Gulf coasts.

There are also a number of studies that consider a Demand Surge effect, but mainly concentrate on estimating the total damages of catastrophe events. For example, Hallegatte (2008) proposes an adaptive regional input-output (ARIO) model, which is used to simulate the economic consequences to the landfall of Hurricane Katrina in Louisiana including Demand Surge effects.

3.5.3.1 Hallegatte et al. (2008)

Hallegatte et al. (2008) provide an analysis of the increasing reconstruction costs in the aftermath of the 2004 and 2005 hurricane seasons in Florida. Their analysis reveals that Demand Surge was the driving force behind the rapid increase in reconstruction prices with a rise of up to 60%. It is noteworthy that they focus only on wages, neglecting the price increases of building products, which is in line with our findings (see Section 3.4). Their most important determinants are the total amount of loss and the pre-existing economic situation prior to the hurricanes, which was in good health before the event. Their proposed model is based on a process of worker migration in response to price signals and calibrated against data on 14 Floridian cities collected by RMS. This is able to reproduce the observed price evolution. However, the model results are not verified for other catastrophes.

As their key explanatory mechanism Hallegatte et al. (2008) assume that Demand Surge is driven by the excess demand for qualified labor in the construction sector and limited by worker migration. To this end, it is necessary to get an impression when and how qualified workers move to a catastrophe affected region. This process of worker migration, in turn, depends on three criteria: (i) the price reaction in the construction sector to market imbalances, (ii) the workers attitude to move, and (iii) the cost of moving, e.g., transportation and accommodation costs. The derived theoretical model is quite able to copy the actual historical price evolution with respect to geographical differences amongst the 14 Floridian cities and the temporal evolution, as can be seen in Figure 3.6.

Based on the calibrated model Hallegatte et al. (2008) try to figure out driving forces of the rising reconstruction costs. One major observation is that the regional reconstruc-

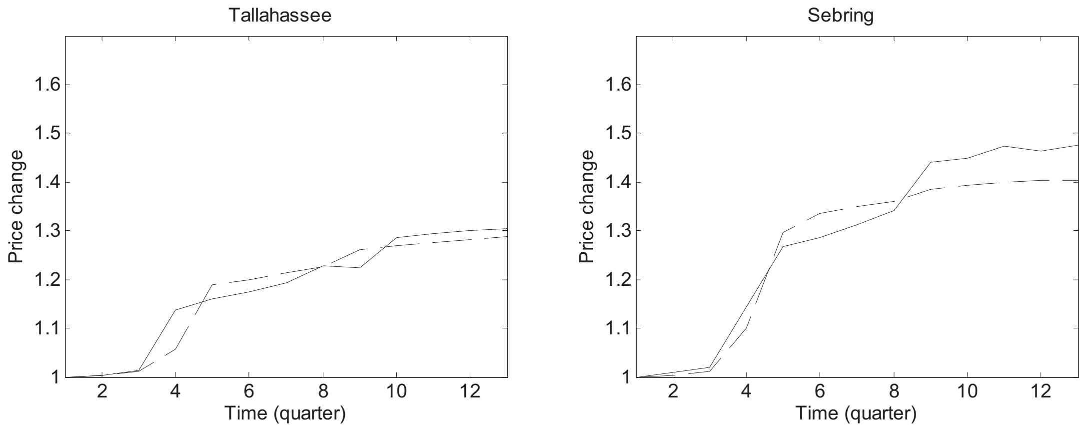

Figure 3.6: Actual and Modeled Reconstruction Price Evolution in Tallahassee and Sebring from Q1 2004 to Q4 2006. Source: Hallegatte et al. (2008).

The continuous lines refer to the actual price evolution, whereas the dashed lines refer to the modeled price evolution.

tion capacity changed between -12% and 60% due to worker migrations one year after the 2004 hurricane season. This change in labor supply corresponds with demand, i.e., labor supply increased where demand is large. Moreover, the model is able to identify important drivers of Demand Surge. Generally speaking, there are two main groups of characteristics: the total amount of loss associated with a catastrophe and the pre-storm situation. Figure 3.7 shows the total Demand Surge in Florida as a function of structure losses. Notably is the observed saturation effect: total Demand Surge rises if structure losses rise, but if structure losses become even larger, the slope decreases. Though, the shape of Demand Surge does not only depend on the structure losses. If the same amount of loss is distributed over a larger area, the imbalance between demand and supply is reduced, and, therefore, Demand Surge is less pronounced. Regarding the influence of the pre-storm situation three different factors can be distinguished: (i) the landfall of several hurricanes within one season, (ii) a reconstruction backlog from other hurricanes, and (iii) the pre-existing economic condition in the affected counties.

3.5.3.2 Olsen and Porter (2011a)

One of the most sophisticated analyses of Demand Surge is provided by Olsen and Porter (2011a). Based on nine Atlantic hurricane seasons the cost changes for six baskets of repairs at 52 cities on the Atlantic and Gulf coasts are calculated as follows:

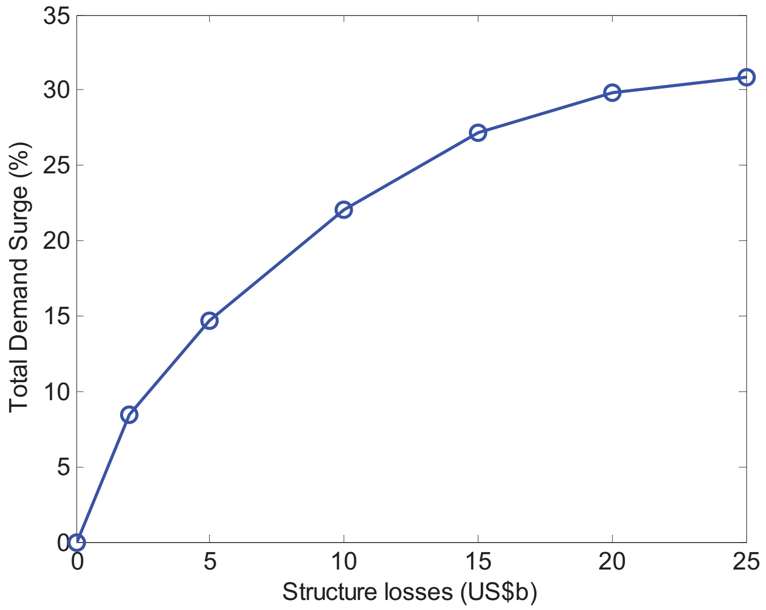

Figure 3.7: Total Demand Surge as a Function of Structure Losses. Source: Hallegatte et al. (2008).

$$relative\ cost\ change = \frac{(final\ cost) - (initial\ cost)}{initial\ cost}. \tag{3.6}$$

Each cost change is calculated from July to January, and, hence, reflects the potential influence of a hurricane season on different baskets of repairs. These six baskets of repairs represent the total repair cost, material components, and labor components and are constructed both for residential and commercial properties.[57] Thus, Olsen and Porter (2011a) refer to the second definition of Demand Surge mentioned in Section 3.1. The empirical results show that changes in labor costs are the driving force of increasing repair costs. In addition, the price changes for the three baskets regarding residential properties are more volatile than the corresponding baskets for commercial properties. Key explanatory variables of their models are: (i) the largest gradient wind speed in a hurricane season, (ii) the number of tropical storms within a hurricane season, and (iii) cost changes in the first half of the year. Thus, in their analysis they focus primarily on physical variables, such as gradient wind speed, and not on the economic mechanisms

[57] The distinction between residential and commercial properties is in line with the procedure of EQE-CAT. See Section 3.5.1.2.

that underlie Demand Surge. Their final multilevel models, including the three variables mentioned above, are able to explain roughly half of the variation in cost change. Based on the Akaike information criterion (AIC)[58] the best model for each basket of repairs is selected. For the total repair cost and the labor components basket all three key explanatory variables are statistically significant. In contrast, for the material component baskets the best models do not contain variables for the maximum wind speed and the number of proximate storms. This underpins the observation that prices for building materials are more or less unaffected by natural disasters.

3.5.3.3 Catastrophe Models including Demand Surge

As already mentioned, many scientific articles focus on the quantification of economic damages of natural disasters, e.g., Cavallo et al. (2010) or Toya and Skidmore (2007). Rather astonishingly, only some consider Demand Surge effects which lead to an inflation in direct costs. Against this background, only articles incorporating Demand Surge effects will be discussed here.

Hallegatte (2008) proposes an ARIO model to simulate the economic costs and response of natural disasters. Its innovations include the consideration of sector production capacities, forward and backward propagations within the economic system, and the introduction of adaptive behavior. The ARIO model includes Demand Surge, which is defined by Hallegatte (2008) as price increases in the construction sector for building products and services. These price effects are driven by a massive imbalance between demand and supply in the construction sector (pull inflation). Based on simulations, a Demand Surge effect of 13% is calculated with respect to Hurricane Katrina, leading to an increase in reconstruction costs from 107 billion US-$ to 121 billion US-$. But the most important result is non linearity between direct losses and total economic losses. Nevertheless, Hallegatte (2008) mentions that Demand Surge has positive consequences, too. The increased wage level attracts additional workers from neighboring regions and

[58] The AIC is a fit measure used for model selection in econometric analyses. Similar to the adjusted R^2 the AIC ceteris paribus penalizes a model if its size, measured in terms of model parameters, increases. See Greene (2012).

leads to a decrease in underproduction. As a consequence, reconstruction work is performed more quickly. A modified version of the above described ARIO model can be found in Hallegatte (2014). The therein described ARIO inventory model focuses more on indirect losses and analyzes their potential drivers.

3.6 Measurement of Demand Surge

In the following, our objective is to analyze the consequences of Demand Surge and to define measures of Demand Surge. For this purpose, we examine catastrophe related payments for reconstruction, resulting from the demand quantities of building materials or services and their prices. As already mentioned in Section 3.4, the focus is on wage payments for workers. We consider a discrete time model with points in time t = 0, 1, ..., T, where t = 0 denotes the point in time of the occurrence of the catastrophe and T is the point in time of the last damage repair. In this context, x(t) denotes the (realized) demand quantity of workers at time t and p(t) stands for the corresponding wage level. Consequently, z(t) = x(t)·p(t) represents the wage payments at time t. In order to evaluate the wage payments, we consider exogenously given capital costs r and an information set Φ available at t = 0, which leads to the following market value of catastrophe related wage payments (with P(1,T) := (p(1), ..., p(T))):[59]

$$V\left(P(1,T)|\Phi\right) = \sum_{t=1}^{T} \frac{E(x(t)\cdot p(t)|\Phi)}{(1+r)^t}. \tag{3.7}$$

While the quantity x(t) is exogenously given by the physical catastrophe damages, the immense demand for workers can lead to a wage increase from a "normal" wage development $P_{\textit{no-cat}}(1,T)$ to a catastrophe induced wage development $P_{cat}(1,T)$. Against this background, we are interested in the impact of the wage increase on the value of wage payments. In order to quantify the impact of a catastrophe induced wage change, we

[59] E(Y|Φ) denotes the expectation value of Y conditional on the information set Φ.

use the following definition (with P(0) := (p(1) = p(0), ..., p(T) = p(0)) standing for no change in the wage development):

$$\zeta = \frac{V\left(P_{cat}(1,T)|\Phi\right)}{V\left(P(0)|\Phi\right)} - \frac{V\left(P_{no\text{-}cat}(1,T)|\Phi\right)}{V\left(P(0)|\Phi\right)}. \tag{3.8}$$

Since $V(P(1,T)|\Phi)/V(P(0)|\Phi)-1$ is the relative change of the market value when switching from the current wage level P(0) to any future wage level P(1,T), the difference ζ measures the increase of the market value when switching the wage level from a no-catastrophe to a catastrophe scenario. Thus, ζ measures only the impact of the catastrophe induced wage increase, excluding business cycle effects. Because the wage level at t = 0 is unaffected by the catastrophe, the difference simplifies to

$$\zeta = \frac{V(\Delta P(1,T)|\Phi)}{V(P(0)|\Phi)} \tag{3.9}$$

with

$$V\left(\Delta P(1,T)|\Phi\right) = \sum_{t=1}^{T} \frac{E(x(t)\cdot \Delta p(t)|\Phi)}{(1+r)^t} = \sum_{t=1}^{T} E\left(\frac{x(t)}{(1+r)^t}\cdot \Delta p(t)\middle|\Phi\right) \tag{3.10}$$

and

$$\Delta p(t) = p_{cat}(t) - p_{no\text{-}cat}(t) \tag{3.11}$$

as the so-called **absolute Demand Surge** at time t. In order to analyze the impact of the Demand Surge on the difference ζ, it is necessary to isolate Δp(t) from x(t) because the quantities x(t) are not representative for all possibly concerned parties, like governments, insurance companies, or building contractors. Although the isolation of the Demand Surge is not immediately possible on the basis of equation 3.9, it is feasible to determine lower and upper bounds of ζ. For this purpose, we assume that x(t) and Δp(t) are non negatively correlated for all t as well as $E(x(t)/(1+r)^t|\Phi)$ and $E(\Delta p(t)|\Phi)$ are non negatively correlated over time.[60] Furthermore, we assume $\sum_{t=1}^{T}(x(t)/(1+r)^t)\cdot p(0) \in \Phi$

[60] The assumption seems to be plausible because an increased demand for workers should lead, on average, to an increase in wages.

to be certain at t = 0.[61] On this basis we get:[62]

$$\frac{1}{T}\sum_{t=1}^{T} E\left(\frac{\Delta p(t)}{p(0)}\middle|\Phi\right) \leq \zeta \leq E\left(max_{t\in\{0,\ldots,T\}}\frac{\Delta p(t)}{p(0)}\middle|\Phi\right). \tag{3.12}$$

Finally, we define

$$\Delta\pi(t) = \frac{\Delta p(t)}{p(0)} = \frac{p_{cat}(t)}{p_{cat}(0)} - \frac{p_{no\text{-}cat}(t)}{p_{no\text{-}cat}(0)} \tag{3.13}$$

as the **(relative) Demand Surge** at time t. Thus, the lower bound in 3.12 represents the average Demand Surge effect:

$$average\ Demand\ Surge = \frac{1}{T}\sum_{t=1}^{T} E\left(\frac{\Delta p(t)}{p(0)}\middle|\Phi\right) \tag{3.14}$$

and the upper bound stands for the maximum Demand Surge effect:

$$maximum\ Demand\ Surge = E\left(max_{t\in\{0,\ldots,T\}}\frac{\Delta p(t)}{p(0)}\middle|\Phi\right). \tag{3.15}$$

In the following Chapters 4 and 5, we will use these general definitions of Demand Surge and make assumptions regarding the unknown parameters. Moreover, we will describe the empirical implementation in detail.

[61] This assumption is based on the subsequent empirical analyses in Chapters 4 and 5, where the value of total costs is an explanatory variable that is contained in our data set.
[62] The proof of the following inequalities is presented in Appendix 3.7.1.

3.7 Appendix

3.7.1 Proof of Inequality 3.12

On the one hand, x(t) and Δp(t) are assumed to be non negatively correlated for each point in time t, i.e.:

$$\frac{E(x(t)\cdot\Delta p(t)|\Phi)}{(1+r)^t} \geq \frac{E(x(t)|\Phi)}{(1+r)^t}\cdot E\left(\Delta p(t)|\Phi\right) \text{ for all t} \in \{1, ..., \text{T}\}. \tag{3.16}$$

On the other hand, $E\left(x(t)/(1+r)^t|\Phi\right)$ and $E\left(\Delta p(t)|\Phi\right)$ are assumed to be non negatively correlated over time implying

$$\frac{1}{T}\sum_{t=1}^{T} E\left(\frac{x(t)}{(1+r)^t}\middle|\Phi\right)\cdot E\left(\Delta p(t)|\Phi\right) \geq \frac{1}{T}\sum_{t=1}^{T} E\left(\frac{x(t)}{(1+r)^t}\middle|\Phi\right)\cdot\frac{1}{T}\sum_{t=1}^{T} E\left(\Delta p(t)|\Phi\right). \tag{3.17}$$

On the basis of 3.10 the inequalities 3.16 and 3.17 imply that a lower bound can be determined as follows:

$$\begin{aligned} V\left(\Delta P(1,T)|\Phi\right) &\geq \sum_{t=1}^{T} E\left(\frac{x(t)}{(1+r)^t}\middle|\Phi\right)\cdot\frac{1}{T}\cdot\sum_{t=1}^{T} E\left(\Delta p(t)|\Phi\right) \\ \Leftrightarrow \frac{V\left(\Delta P(1,T)|\Phi\right)}{V\left(P(0)|\Phi\right)} &\geq \frac{\frac{1}{T}\cdot\sum_{t=1}^{T} E(\Delta p(t)|\Phi)}{p(0)}. \end{aligned} \tag{3.18}$$

Using the abbreviation $\Delta p_{max} = max_{t\in\{0,...,T\}}\Delta p(t)$ leads to

$$\begin{aligned} V\left(\Delta P(1,T)|\Phi\right) &= \sum_{t=1}^{T} E\left(\frac{x(t)}{(1+r)^t}\cdot\Delta p(t)\middle|\Phi\right) \\ &\leq \sum_{t=1}^{T} E\left(\frac{x(t)}{(1+r)^t}\cdot\Delta p_{max}\middle|\Phi\right) \\ &= E\left(\sum_{t=1}^{T}\frac{x(t)\cdot p(0)}{(1+r)^t}\cdot\frac{\Delta p_{max}}{p(0)}\middle|\Phi\right) \\ &= \sum_{t=1}^{T}\frac{x(t)\cdot p(0)}{(1+r)^t}\cdot\frac{E(\Delta p_{max}|\Phi)}{p(0)}. \end{aligned} \tag{3.19}$$

The latter equality results from the assumption $\sum_{t=1}^{T} x(t) \cdot p(0)/(1+r)^t \in \Phi$. Against this background, we also get $V(P(0)|\Phi) = \sum_{t=1}^{T} x(t) \cdot p(0)/(1+r)^t$. Thus, equation 3.19 is equivalent to

$$\frac{V\left(\Delta P(1,T)|\Phi\right)}{V\left(P(0)|\Phi\right)} \leq \frac{E(\Delta p_{max}|\Phi)}{p(0)}, \tag{3.20}$$

which provides an upper bound and completes the proof.

4 Insured Loss Inflation and Demand Surge

4.1 Fundamentals and Research Questions

In the aftermath of a natural disaster, there is increased demand for skilled reconstruction labor, which leads to significant increases in reconstruction labor costs, and, hence, insured losses. Such inflation effects are known as Demand Surge effects as described in Section 3.1. It is important for insurance companies to properly account for these effects when calculating insurance premiums and determining economic capital. The main objective of this chapter is to propose an approach to quantify the Demand Surge effect in an empirical setting. As described in Section 3.5 there are only a few contributions in the literature that address this phenomenon. Unfortunately, these models consider Demand Surge exclusively on a qualitative level or only for a specific catastrophe type or event; universally valid quantitative models for Demand Surge have not been published. Against this background, the following important tasks regarding catastrophe induced insured loss inflation will be analyzed in this chapter:

- How can Demand Surge effects be quantified in an empirical setting?
- Which are the key drivers of this phenomenon?

In this way, this chapter provides a basis for the quantitative assessment of Demand Surge for future catastrophes, which is important, on the one hand, for insurance companies, as already described. On the other hand, such information is also relevant for investors of insurance stocks and issuers and investors of catastrophe linked securities (such as Cat Bonds), who have to consider Demand Surge within the framework of security pricing. The established empirical analysis is based on two papers written by Döhrmann et al. (2013a) and Döhrmann et al. (2013b).

4.2 Hypotheses

In the literature, common themes of Demand Surge are discussed but have not yet been tested empirically.[63] Most obvious is the potentially positive impact of damages on Demand Surge. More severe catastrophes lead to increasing costs and a stronger imbalance between demand and supply for construction labor. As a consequence, labor prices rise, and the Demand Surge effect is more pronounced.[64] Thus, we hypothesize the following:

> *Damage Hypothesis (H1): The magnitude of the Demand Surge strongly increases with the total amount of repair work.*

It is important to mention that an isolated examination of a catastrophe is not adequate. A possible backlog from previous events worsens the situation, and the same effect is likely for subsequent damages from other events. For example, AIR Worldwide Corporation (2009a) aggregates some catastrophes into one single large event and assumes that reconstruction begins only after these events occurred. In addition, Hallegatte et al. (2008) simulate a cumulative Demand Surge level of 37% in Florida for the 2005 season compared to 24% if no hurricane had occurred in 2004. Therefore, it is necessary to explicitly consider alternative catastrophes with close temporal and spatial proximity. Hence, in compliance with the literature, we expect the following:

> *Proximity Catastrophe Hypothesis (H2): The magnitude of the Demand Surge increases with other catastrophes with close temporal and spatial proximity.*

If the total number of claims per event rises, the procedure of insurance claims handling might suffer for two reasons. First, politics might put pressure on insurance companies to settle claims quickly. As a consequence, claim adjusters spend less time for each

[63] See Hallegatte et al. (2008) and Olsen and Porter (2011b).
[64] See Hallegatte et al. (2008), Krutov (2010), and Olsen and Porter (2011b).

assessment. Alternatively, insurance companies might install untrained claim adjusters. Both lead to poorer damage assessments and typically increased payments.[65] Regarding the 1994 Northridge earthquake Wiggins (1996) notes that insurance claims were overpaid by as much as a factor of two. Among other reasons, Wiggins (1996) mentions improperly trained adjusters. Secondly, in highly competitive markets, insurance companies may be classified by the insured and the media according to the ways in which they settle their claims, which could have a significant impact on their future premium income.[66] For example, RMS (2000) finds that insurance companies did not verify claims under a given threshold in the aftermath of the 1999 Windstorms Lothar and Martin in France.[67] In line with this finding, insurers heavily affected by the 1999 Windstorm Anatol in Denmark were handling claims up to an amount of DKK 10,000 by telephone only. Though, claimants were forced to provide a photography of the insured damage before repairing could start.[68] As a consequence, insurance companies might settle claims that are not attributable to the catastrophe itself due to fraud. With respect to Anatol a study estimates that approximately 10% of total claims payment are attributable to insurance fraud.[69] In summary, both aspects lead to increasing reconstruction demand. Although a part of the uninsured damage might be repaired even without insurance, the reconstruction work would be distributed over a longer time period.[70] Thus, we hypothesize the:

> *Insurance Hypothesis (H3): A larger number of insurance claims per event lead to higher Demand Surge levels.*

If the economy in the construction sector is growing, idle capacities diminish, and the disequilibrium between demand and supply results in labor cost increases. In a simulation study, Hallegatte et al. (2008) show that the Demand Surge for the 2004 and

[65] See Thomas (1976).
[66] See Olsen and Porter (2010, p. 13 ff.).
[67] Abraham et al. (2000) report a number of 3 million claims in the aftermath of Windstorms Lothar and Martin in France. As claim adjusters were a scarce resource during that time some insurers applied a threshold of 7,725 US-$ for claims to be assessed.
[68] See Souch (2010).
[69] See Souch (2010).
[70] Olsen and Porter (2010) provide a detailed discussion of the different issues insurance companies were confronted with in the reconstruction period following the 1906 San Francisco earthquake and fire. Besides issues related to insurance fraud and claims handling, the role of the media and public on insurance behavior is discussed in detail.

2005 hurricane seasons in Florida would have been much lower if the economy had been in a recession, as was the case during the landfall of Hurricane Andrew in 1992. Against this background, we expect the:

Growth Hypothesis (H4): In a stage of growth for the economy, Demand Surge levels are higher.

A larger number of establishments in the construction sector leads to competition and, consequently, keeps labor prices low.[71] Moreover, capacity adjustments are easier to conduct given an already large number of establishments in the construction sector because both equipment and organizational structures are already available. Therefore, we propose the contractor hypothesis:

Contractor Hypothesis (H5): A larger number of building contractors have a restraining effect on Demand Surge.

If wage levels are already high due to a construction boom or a backlog from previous catastrophes, further labor price increases might be lessened. Thus, there could be saturation effects. With each additional price increase by a single US-$, a growing number of workers are addressed. Starting with workers who commute to work and are attracted by increased labor prices in the catastrophe region, ongoing labor price increases attract additional workers who at least temporary transfer their residence. This second group is significantly larger than the first group and increases the possible labor supply substantially. Altogether, this leads to a new equilibrium state. Hallegatte et al. (2008) observe a similar effect regarding structural losses. Their simulated Demand Surge level increases with growing losses, but the slope decreases as losses become even larger. Another reason for saturation effects might be that, in the case of extended replacement cost coverage, insurance policy limits are generally capped between 20% and 25% in excess of the policy limit.[72] As already mentioned in Section 3.4, labor prices are the driving force behind the rising cost of reconstruction after catastrophes. If wage levels already increased in the past, cumulative price increases of more than 20% to 25% compared to a baseline scenario are plausible. In this case, policyholders have to pay these extra repair costs on their own and might delay further repairs, reducing the overall demand. In a nutshell, we expect the following:

[71] See Olsen and Porter (2011b).
[72] See Danise (2013).

Saturation Hypothesis (H6): Higher wage levels in the construction sector lessen Demand Surge due to saturation effects.

4.3 Empirical Analysis

Consecutively, we test our hypotheses from Section 4.2, which refer to the impact of catastrophe-specific variables and macroeconomic conditions on Demand Surge. In addition, we will convert the theoretical considerations in Section 3.6 into an empirical setting and derive an approach to quantify the Demand Surge effect. Regarding catastrophe data we rely on data provided by EM-DAT and SHELDUS[73] (Spatial Hazard Events and Losses Database for the United States). Both data sets are comparable in the sense that they contain detailed information regarding natural catastrophes in the United States. Nevertheless, there are some crucial differences in the construction of both. EM-DAT catastrophe data are provided on an event basis, meaning that each observation relates to one major disaster, e.g., Hurricane Katrina. In contrast, SHELDUS observations are collected on the lower level of catastrophe regions. As a consequence, the number of observations in SHELDUS is significantly larger. Empirical results regarding catastrophe data provided by EM-DAT are presented in Section 4.3.2, whereas Section 4.3.3 replicates the results for SHELDUS data. A critical discussion of the empirical analyses and conformities and nonconformities between EM-DAT and SHELDUS data can be found in Section 4.4.

4.3.1 Quantifying Demand Surge

Within this Chapter 4 we will calculate the Demand Surge effect from an insurer's point of view. Therefore, the introduced measurement approach in Section 3.6 has to be adapted

[73]SHELDUS: The Spatial Hazard Events and Losses Database for the United States - http://www.sheldus.org - University of South Carolina - Columbia - United States.

to the special needs of an insurance company. As described in Section 3.3 insurers have to deal with inflating claim levels in case of disasters and have to pay additional costs for materials and services. In Section 3.4 we additionally characterized the price evolution of building materials and services in case of natural disasters and concluded that price effects of building materials are negligible. Thus, an insurer has to estimate claims payments for future catastrophes including Demand Surge effects which are attributable to increasing reconstruction labor costs. If we assume a constant proportion $1 - \rho$ of total repair costs to be attributable to materials, we can derive the following valuation approach:[74]

$$claims\ payment_{cat} = \sum_{t=1}^{T} \sum_{j=1}^{i(t)} claims\ payment_{no\text{-}cat}(j) \cdot (1 + \rho \cdot \Delta\pi(t)), \tag{4.1}$$

where $i(t)$ denotes the number of settled claims at time t, T denotes the point in time of the last settled claim, and $\Delta\pi(t)$ is defined according to equation 3.13 as the (relative) Demand Surge at time t.

If we additionally assume that the settled claims payments are constant over time we can ease equation 4.1 further:

$$\begin{aligned} claims\ payment_{cat} &= claims\ payment_{no\text{-}cat}^{per\ period} \cdot \sum_{t=1}^{T} (1 + \rho \cdot \Delta\pi(t)) \\ &= claims\ payment_{no\text{-}cat}^{per\ period} \cdot T \cdot \frac{1}{T} \cdot \sum_{t=1}^{T} (1 + \rho \cdot \Delta\pi(t)) \\ &= claims\ payment_{no\text{-}cat}^{per\ period} \cdot T \left[1 + \rho \cdot \frac{1}{T} \cdot \sum_{t=1}^{T} \Delta\pi(t) \right] \\ &= claims\ payment_{no\text{-}cat}^{per\ period} \cdot T \cdot [1 + \rho \cdot avg.\ Demand\ Surge]\,. \end{aligned} \tag{4.2}$$

We measure Demand Surge on the basis of catastrophe events in the United States that are prone to Demand Surge. For this purpose, we use catastrophe data provided by two different vendors: EM-DAT and SHELDUS. Because relatively small catastrophes

[74] For an exemplary breakdown of total repair costs by building components see AIR Worldwide Corporation (2009a, p. 22).

are less likely to produce the increasing labor demand that creates Demand Surge effects, we use a cut-off value of 100 million US-$ for events in the sample.

One problem for the measurement of Demand Surge is that the price level in the no-catastrophe scenario $p_{no-cat}(t)$ is not observable. However, it is possible to estimate the wage level at time t in the no-catastrophe scenario using the assumption

$$\frac{p^{(A)}_{\textit{no-cat}}(t) - p^{(A)}_{\textit{no-cat}}(0)}{p^{(A)}_{\textit{no-cat}}(0)} = \frac{p^{(B)}_{\textit{no-cat}}(t) - p^{(B)}_{\textit{no-cat}}(0)}{p^{(B)}_{\textit{no-cat}}(0)}, \tag{4.3}$$

where (A) denotes a catastrophe affected region and (B) a non-affected region. In this context, region (B) is similar to (A) in all respects except for the exogenous event which is a natural catastrophe in our case. This is basically the standard assumption of the difference-in-differences approach.[75] Thus, the wage level in region (A) at time t in the no-catastrophe scenario can be calculated in the following manner:

$$p^{(A)}_{\textit{no-cat}}(t) = \left(1 + \frac{p^{(B)}_{\textit{no-cat}}(t) - p^{(B)}_{\textit{no-cat}}(0)}{p^{(B)}_{\textit{no-cat}}(0)}\right) \cdot p^{(A)}_{\textit{no-cat}}(0). \tag{4.4}$$

Against this background, we rewrite equation 3.13 as follows:

$$\textit{Demand Surge}(t) = \frac{p^{(A)}_{\textit{cat}}(t)}{p^{(A)}_{\textit{cat}}(0)} - \frac{p^{(A)}_{\textit{no-cat}}(t)}{p^{(A)}_{\textit{no-cat}}(0)} = \frac{p^{(A)}_{\textit{cat}}(t)}{p^{(A)}_{\textit{cat}}(0)} - \frac{p^{(B)}_{\textit{no-cat}}(t)}{p^{(B)}_{\textit{no-cat}}(0)}, \tag{4.5}$$

and obtain our measures for the (relative) average and maximum Demand Surge:

$$\begin{aligned} \textit{average Demand Surge} &= \frac{1}{T}\sum_{t=1}^{T} \frac{p^{(A)}_{\textit{cat}}(t) - p^{(A)}_{\textit{no-cat}}(t)}{p^{(A)}_{\textit{no-cat}}(0)} \\ &= \frac{1}{T}\sum_{t=1}^{T} \left\{ \frac{p^{(A)}_{\textit{cat}}(t)}{p^{(A)}_{\textit{cat}}(0)} - \frac{p^{(B)}_{\textit{no-cat}}(t)}{p^{(B)}_{\textit{no-cat}}(0)} \right\}, \end{aligned} \tag{4.6}$$

$$\textit{maximum Demand Surge} = max_{t\in\{0,\ldots,T\}} \left\{ \frac{p^{(A)}_{\textit{cat}}(t)}{p^{(A)}_{\textit{cat}}(0)} - \frac{p^{(B)}_{\textit{no-cat}}(t)}{p^{(B)}_{\textit{no-cat}}(0)} \right\}. \tag{4.7}$$

[75] See Ashenfelter and Card (1985) and Wooldridge (2013, p. 438 ff.).

To calculate the average Demand Surge effect for each catastrophe in the sample, we use equation 4.6. Unfortunately some of the necessary data for the calculation cannot directly be observed. This is the case for T, and the composition of the labor price index p(t) is not known in advance and depends on the type of catastrophe. Moreover, it is unclear which region (B) should be chosen so that the difference-in-differences assumption from equation 4.3 holds.

Regarding the choice of T, we will test different values because the date of the last settled claim is not known publicly. McCarty and Smith (2005) analyze the 2004 hurricane season in Florida and find that, one year later, only 35% of the damaged units were totally repaired. Moreover, in 16% of the cases, reconstruction had not even been started, which might suggest that a time slot of one year and a corresponding value of $T = 1$ might be too short for our purposes. In addition, Belasen and Polachek (2008) state that even damages from the largest catastrophes in the past were repaired within 2 years. However, catastrophe claims are generally considered to be short tailed,[76] and Gron (1994) argues that from 1977 to 1986, 95% of homeowners' claims in the United States were paid within 3 years. In addition, Hallegatte et al. (2008) state that 94% and 91% of the 2004 and 2005 claims in Florida are assumed to be paid until August 2006, meaning that almost all claims were settled within 2 years. Against this background, we test three different values of T, with $T = 1$ being a lower bound, $T = 3$ being an upper bound, and $T = 2$ being our reference.

To measure Demand Surge for the considered catastrophes, we additionally require a price index p(t) that refers to the labor price increase in the construction sector for each catastrophe area. We model the price index p(t) in each catastrophe area using the retail labor index of Xactware, a member of Verisk Analytics, Inc. Xactware offers pricing information in the construction sector for 467 economic areas in the United States and Canada and has published a retail labor index on a quarterly basis since 2002 and on a monthly basis since 2009 for each of these areas.[77] The contained retail labor index is quite similar to building services chosen by AIR Worldwide Corporation (2009a)

[76]See, for instance, Harrington (1997) and Gron (1994).
[77]See Xactware (2012).

for reconstruction after storm losses. A detailed composition of the retail labor index is available in Table 4.1. Xactware's pricing research and methodology is based on an iterative, five phased process described in Xactware (2014). Of crucial importance are, of course, reliable market prices that stem from various sources including: "thousands of in-field estimates that are submitted to Xactware every day (i.e. estimates actually used to settle claims); market surveys of industry professionals; retail pricing research; unit-price research based on surveys with over 100,000 contractors, insurance carriers, and independent adjusters; pricing feedback from in-field users; independent pricing verification requests; customer-specific cost data; catastrophe-specific pricing research; additional research surveys; multiple third-party sources for data such as workers' comp [ensation], federal taxes, state taxes, local taxes, and so on; many other research initiatives".[78]

Table 4.1: Composition of the Retail Labor Index.

Composition	
Carpenter - Finish, Trim/Cabinet	Heating/A.C. Mechanic
Carpenter - General Framer	Insulation Installer
Carpenter - Mechanic	General Laborer
Cleaning Technician	Mason Brick/Stone
Floor Cleaning Technician	Plasterer
Concrete Mason	Plumber
Drywall Installer/Finisher	Painter
Electrician	Roofer
Equipment Operator	Tile/Cultured Marble Installer
Flooring Installer	

Unfortunately, the localizations of the analyzed catastrophes provided by EM-DAT/SHELDUS are usually not consistent with pricing information for the economic areas of the Xactware data. Because we are interested in the labor price increase in the center of each catastrophe region specified by EM-DAT/SHELDUS, we retrieve the geographic coordinates in WGS84 (World Geodetic System, dating from 1984 and last revised in 2004) of all localizations in our EM-DAT/SHELDUS sample and compute the closest Xactware localization available (the shortest distance between two points on the surface

[78] See Xactware (2014).

of a sphere) for each of them.[79] Then, we retrieve the corresponding retail labor index time series for this Xactware localization.

To segregate the relative wage increase due to a catastrophe from alternative influencing factors, we apply equation 4.5. Thus, we first calculate the relative change of wage in the catastrophe affected region (A), i.e., $\frac{p_{cat}^{(A)}(t)-p_{cat}^{(A)}(0)}{p_{cat}^{(A)}(0)}$ where t = 0 refers to the point in time of the occurrence of the catastrophe. As the wage evolution over time is affected by the general economic trend and cyclical variations, we have to isolate the catastrophe induced change in wage form other possible influencing factors. Therefore, we normalize the actual time series with respect to the wage evolution in the case no catastrophe had occurred (the counterfactual). Against this background, we choose the aggregated time series for the United States as a proxy for the hypothetical relative change in wage in the no-catastrophe scenario $\frac{p_{no\text{-}cat}^{(B)}(t)-p_{no\text{-}cat}^{(B)}(0)}{p_{no\text{-}cat}^{(B)}(0)}$ based on the assumption that the two above mentioned effects are both contained in the nationwide index. Of course, this choice is questionable but the task to identify an alternative region (B) being similar to the catastrophe region (A) in as many respects as possible is problematic for two reasons.[80] First, it is reasonable to assume that the regions most similar to (A) are located nearby. Unfortunately, these regions are usually affected by the same catastrophe event, too. Second, the prerequisite for a region to be non-catastrophic is that neither in the region itself nor in the greater area a catastrophe occurred in the time period from two years before to two years after the event.[81] As a consequence, according to our dataset nearly all regions are catastrophe affected. Thus, the choice of the nationwide index seems plausible, as the effects of single catastrophes on the aggregate nationwide index can be regarded as negligible. Afterwards, we calculate the difference between both relative changes and assume that the gap between both is completely attributable to Demand Surge. Finally, we calculate the average and maximum Demand Surge for time periods of T = 1, 2, and 3 years based on equations 4.6 and 4.7. An exemplary calculation of

[79] See Appendix 4.5.1 for a detailed description of the mapping algorithm.

[80] Nevertheless, this task could be conducted with the help of a propensity score matching. For further information about this statistical matching technique see Rosenbaum and Rubin (1983).

[81] In the following chapters, we will identify a radius of 300 km and 450 km to be adequate to define the greater area in which alternative catastrophes influence the wage evolution of the center.

this procedure with respect to the landfall of Hurricane Frances in West Palm Beach (Florida) in Q3 2004 is shown in Figure 4.1.

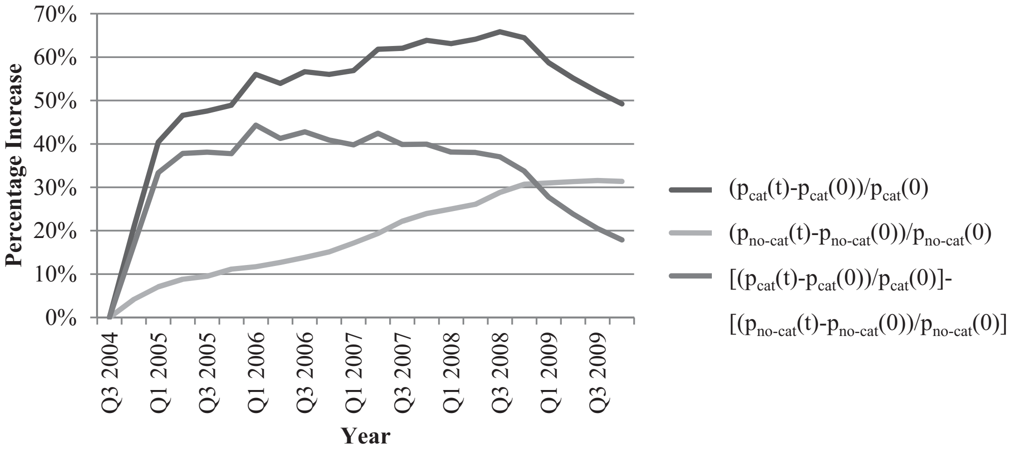

Figure 4.1: Demand Surge Measurement.

In this figure our measurement of Demand Surge is depicted. We compute the percentage increase of the retail labor price index in West Palm Beach (p_{cat}) and the entire US ($p_{\text{no-cat}}$) starting directly before the landfall of Hurricane Frances in West Palm Beach in Q3 2004. In a second step, we calculate the difference between both time series of percentage increases according to equation 4.5. Finally, we calculate the mean value over varying time periods of 1, 2, and 3 years.

4.3.2 EM-DAT Catastrophe Database

The EM-DAT catastrophe database contains all natural and man-made catastrophes since 1900.[82] The database is composed of data filed in by United Nations (UN) agencies, non-governmental organizations, insurance companies, research institutes, and press agencies.[83] All damage values therein are expressed in US-$ at the time the events took place and are converted in 2005 US-$ using the United States' Consumer Price Index (CPI) for comparison. Furthermore, all of these values refer to direct damage.[84] Thus, indirect damages, i.e., the reduction of the total value added, are not contained.[85] As

[82]For a description of the disaster definition criteria applied by EM-DAT see Section 2.1.
[83]See Scheuren et al. (2008).
[84]See Scheuren et al. (2008).
[85]See Hallegatte and Przyluski (2010).

already mentioned small catastrophes are less likely to produce the increasing labor demand that creates Demand Surge effects. Thus, we use a cut-off value of 100 million US-$ for events in the sample.

4.3.2.1 Demand Surge Drivers

For the direct damage caused by catastrophes, we rely on data from the EM-DAT database. All damages are reported on an event basis and not on the lower level of catastrophe regions. However, regarding insured property losses, these data are available on the lower level of catastrophe regions. If we assume a constant insurance proportion of direct damages in the catastrophe-affected regions, it is possible to allocate the total direct damage to single catastrophe regions. For information regarding insured property losses, we use data from Property Claims Services (PCS), a unit of Insurance Services Office (ISO). PCS is a catastrophe loss index provider and an authority on insured property losses from catastrophes in the United States. Currently, PCS is the only source of United States insured losses of catastrophic events. For each recorded catastrophe, PCS provides information regarding the estimated insurance payments and the number of claims in different lines of business, e.g., personal and commercial, on the state level. Moreover, their estimates are accepted as triggers in catastrophe-derivative instruments, such as Cat Bonds. On the state level, direct damages are allocated according to their relative share of estimated insurance payments. On the city/county level, these partial damages are uniformly distributed across all localizations. Because different localizations in EM-DAT regarding the same event may be mapped to the same Xactware localization, a reassessment algorithm combines these entries and recalculates the direct damage, which is now the sum of the direct damages already calculated.

To control for the effect of alternative catastrophes with close temporal and spatial proximity, we additionally calculate direct damages in a given radius of 450 km, including direct damages in the same state, around each catastrophe region for different time intervals. In a preliminary analysis, we also tested alternative radii of 150 km, 300 km, and 600 km. As a selection criterion we used the adjusted R^2 of models containing the direct damage variable and direct damages of previous and subsequent catastrophes within each potential radius. We observed that the adjusted R^2 was strictly increasing up to a radius of 450 km, whereas additional damages in a radius of 450 km to 600 km did not create any additional explanatory power. The corresponding results are presented in Table 4.2.[86] Against this background, we assume that the capacity of the construction sector in the catastrophe area can be represented by the number of establishments within a radius of 450 km and is reduced if alternative catastrophes occur with close temporal proximity. We consider catastrophes up to 3 years before or after the end date of each catastrophe, depending on the chosen value of T. Because the availability of labor price data in Xactware starts in 2002, our sample of catastrophes spans the time period of 2002-2010.

To test our insurance hypothesis (H3), we calculate the number of insurance claims for commercial and personal lines of business on an event basis using data from PCS. For this purpose, each entry in EM-DAT was mapped to the corresponding entry in PCS.

To incorporate the state of the economy in the construction sector, we calculate the relative change in the real gross domestic product (GDP) by state in the construction sector before the catastrophe occurred. However, the year in which the catastrophe occurred might already be affected by Demand Surge. To avoid this effect, we calculate the relative change between two and one year before the catastrophe. To this end, we use data from the Bureau of Economic Analysis (BEA), which provides data on an annual basis for each state in the US.

To reflect the supply side of the labor market, we measure the capacity of the construction sector as indicated by the number of establishments. These data were retrieved from the Quarterly Census of Employment and Wages (QCEW), which is compiled by the Bureau of Labor Statistics (BLS). Quarterly data are available for each county, metropolitan statistical area (MSA), and state within the United States.

[86] A brief description of each variable used in the analysis is provided in the subsequent Table 4.3.

Table 4.2: Choice of Radius.

The table reports results of OLS regressions with clustered standard errors regarding the influence of damages in different radii on the average Demand Surge effect in a period of 2 years after the catastrophe. The data set comprises catastrophes with total damage of at least 100 million US-\$. Model (A.1) considers damages within a radius of 150 km, model (A.2) refers to a radius of 300 km, model (A.3) to 450 km, and model (A.4) to 600 km. We report t-statistics in parentheses. The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	(A.1)	(A.2)	(A.3)	(A.4)
Damage	$0.1477^{\dagger}$	0.2204^{***}	0.2165^{***}	0.2169^{***}
	(1.78)	(4.04)	(4.30)	(4.34)
Subsequent damage [0; 0.5)	0.8952^{*}	0.1377^{***}	0.1339^{***}	0.1290^{***}
	(2.06)	(5.85)	(7.13)	(7.55)
Subsequent damage [0.5; 1)	0.2629^{**}	0.2061^{**}	0.1941^{***}	0.1942^{***}
	(2.84)	(3.04)	(3.53)	(3.53)
Subsequent damage [1; 1.5)	0.4358	1.0897^{***}	1.1039^{***}	1.1060^{***}
	(1.58)	(4.42)	(4.71)	(4.71)
Subsequent damage [1.5; 2)	-0.0198	-0.0738	-0.0635	-0.0612
	(-0.22)	(-0.89)	(-0.78)	(-0.77)
Previous damage [0.5; 0)	0.2532	$0.2106^{\dagger}$	$0.1875^{\dagger}$	$0.1892^{\dagger}$
	(1.59)	(1.70)	(1.92)	(1.92)
Previous damage [1; 0.5)	-0.2947	-0.0289	-0.0242	-0.0190
	(-1.54)	(-1.29)	(-1.13)	(-1.17)
Previous damage [1.5; 1)	0.0111	0.0094	0.0192	0.0153
	(0.19)	(0.23)	(0.59)	(0.46)
Previous damage [2; 1.5)	-0.0086	-0.0535	-0.0528	-0.0518
	(-0.30)	(-0.72)	(-0.70)	(-0.70)
Constant	-0.1866	-0.3032	-0.3361	-0.3430
	(-0.73)	(-1.11)	(-1.24)	(-1.27)
Observations	180	180	180	180
Adjusted R^2	0.609	0.700	0.730	0.730

Finally, possible saturation effects are measured by the relative change of the retail labor index of the catastrophe region in the foregoing 18 months before the catastrophe. This time period is chosen to cover preceding price increases due to possible events in the preceding hurricane season.[87] In contrast, a smaller time period could possibly disregard the initial jump in the retail labor price index after a hurricane event and only capture the already high price level, which might show no further price increase.

An overview of the set of exogenous variables used in the upcoming empirical analysis is shown in Table 4.3.

Table 4.3: Variable Definitions.

Variable	Definition
Damage	Direct damage of the catastrophe (in billion US-$).
Subsequent damage [a; b)	Direct damage of subsequent catastrophes that occurred in geographical and temporal proximity (in billion US-$); [a; b) denominates the time period in years with respect to the considered event.
Previous damage [a; b)	Direct damage of previous catastrophes that occurred in geographical and temporal proximity (in billion US-$); [a; b) denominates the time period in years with respect to the considered event.
Claims	Number of insurance claims (in millions).
GDP change	Real GDP growth of the construction sector in the affected state.
Establishments	Number of establishments of the construction industry in the affected county/MSA/state (in thousands).
Wage change	Relative change of wage in the construction sector during the 18 months before the catastrophe.
Mapping distance	Distance between the catastrophe (data from EM-DAT) and the assigned localization of economic variables (data from Xactware) (in km).

[87]The Atlantic hurricane season runs from June 1st through November 30th, spanning a time period of six months. See National Hurricane Center (2014).

4.3.2.2 Descriptive Statistics

Summary statistics of our sample are presented in Tables 4.4 to 4.8. To provide some insights into the composition of the data, we show the distribution of the observations over the full time period of our sample, 2002-2010, along with the type of catastrophe in Table 4.4. It is worth noting that the number of observations is quite uniformly distributed across the years, excluding the unexpectedly high value in 2008. Although total losses during this year were quite moderate, the number of events was the highest since 1998.[88]

Table 4.4: Summary Statistics – Composition of the Data Set.

	Observations	Percentage
Panel A: Year		
2002	13	6.77
2003	22	11.46
2004	19	9.90
2005	17	8.85
2006	18	9.38
2007	22	11.46
2008	45	23.44
2009	24	12.50
2010	12	6.25
Panel B: Type of Disaster		
Flood	23	11.98
Storm	160	83.33
Local Storm	95	49.48
Tropical Cyclone	50	26.04
Extratropical Cyclone (Winter Storm)	2	1.04
Not further specified	13	6.77
Wildfire	9	4.69

In Table 4.5, we present details about the distribution of our set of exogenous variables for the full sample. After excluding all observations with damages of less than 100 million US-$, only 192 of 901 entries remain. The distribution of the damage is highly right skewed, with a mean value of 1.597 billion US-$, a median of 0.2496 billion US-$,

[88] See Insurance Information Institute (2009).

and a maximum of 41.01 billion US-\$. For the calculation of subsequent and previous damages within a radius of 450 km, we choose time intervals of half a year up to 2 years before or after the catastrophe and a one-year interval for the remaining time window of up to 3 years. In more than 50% of all cases, at least one further catastrophe can be observed in each time slot. The number of observations for subsequent damages in the time periods one to one and a half, one and a half to two, and two to three years after the catastrophe are smaller than for all other time windows. This is a direct result of the data availability. As our data set of catastrophe events ends in 2011, we are unable to calculate subsequent damages for the time periods one to one and a half, and one and a half to two years after the catastrophe for observations that end in 2010 and two to three years after the catastrophe for observations that end in 2009 or 2010. Moreover, we find that the GDP change is negative in more than 75% of the cases, which indicates that at the time the catastrophes took place, the construction sector most likely had idle capacities. A maximum wage change of 50.98% during the previous 18 months corresponds to Hurricane Wilma in Naples (Florida) in October 2005. In this case, the foregoing 18 months include the landfalls of Hurricanes Charley, Frances, and Jeanne in Florida, so it is likely that the current wage level was driven strongly by Demand Surge from previous events. With regard to mapping distance, a perfect matching could be achieved in 86% of the cases. In Table 4.6, the number of observations is further limited. The sample now comprises 60 catastrophe regions, with minimum sustained damages of 500 million US-\$. As a consequence, the mean value of the damage variable is significantly higher at 4.639 billion US-\$ compared to Table 4.5. The same observation is true for the number of claims. All other exogenous variables are quite similarly distributed.

In Table 4.7, summary statistics are presented for each measure of Demand Surge, both for large (damage $\geq$ 100 million US-\$) and extreme catastrophes (damage $\geq$ 500 million US-\$). By definition, the maximum Demand Surge effect is larger than the average Demand Surge effect for the two-year time period. Furthermore, in every setting, the distribution is right skewed. For large catastrophes, the mean Demand Surge effect varies between 1.3% and 2.0%, whereas for extreme catastrophes, the Demand Surge effect is more pronounced, varying between 3.3% and 4.7%. The fact that the maxima remain the

Table 4.5: Summary Statistics – Demand Surge Drivers (Damage $\geq$ 100 million US-$).

The sample comprises 192 catastrophe regions with a minimum damage of 100 million US-$. The table shows descriptive statistics of the set of independent variables, which is defined in Table 4.3.

	Obs.	Mean	Std. Dev.	Min.	q25	q50	q75	Max.
Damage (billion US-$)	192	1.597	5.154	0.1020	0.1530	0.2496	0.6272	41.01
Subsq. damage [0; 0.5)	192	1.606	8.450	0	0	0.0639	0.3508	110.99
Subsq. damage [0.5; 1)	192	0.9770	4.985	0	0	0.0385	0.2203	57.34
Subsq. damage [1; 1.5)	180	0.8518	2.781	0	0	0.0516	0.4088	21.90
Subsq. damage [1.5; 2)	180	0.3439	1.187	0	0	0.0667	0.1697	10.29
Subsq. damage [2; 3)	156	2.166	7.134	0	0.0667	0.2089	0.7233	62.48
Prev. damage [0.5; 0)	192	1.123	5.007	0	0	0.0440	0.2413	57.34
Prev. damage [1; 0.5)	192	0.8415	3.957	0	0	0.0795	0.2358	32.57
Prev. damage [1.5; 1)	192	0.5075	3.104	0	0	0.0595	0.1818	30.23
Prev. damage [2; 1.5)	192	0.3769	2.475	0	0	0.0074	0.1007	32.57
Prev. damage [3; 2)	192	1.157	4.966	0	0.0396	0.1764	0.4497	62.48
Claims (millions)	192	0.2757	0.3677	0.0028	0.0579	0.1379	0.2894	1.385
GDP change (in %)	192	-3.799	4.565	-20.74	-6.337	-3.428	-0.8099	6.295
Est. (thousands)	192	18.73	15.85	0.0500	8.161	12.44	26.68	79.90
Wage change (in %)	192	8.624	7.101	0.2013	5.132	6.982	9.509	50.98
Mapping distance (km)	192	4.637	14.40	0	0	0	0	84.19

Table 4.6: Summary Statistics – Demand Surge Drivers (Damage $\geq$ 500 million US-$).

The sample comprises 60 catastrophe regions with a minimum damage of 500 million US-$. The table shows descriptive statistics of the set of independent variables, which is defined in Table 4.3.

	Obs.	Mean	Std. Dev.	Min.	q25	q50	q75	Max.
Damage (billion US-$)	60	4.639	8.502	0.5035	0.6788	1.698	4.576	41.01
Subsq. damage [0; 0.5)	60	2.005	4.329	0	0	0.0585	1.751	21.90
Subsq. damage [0.5; 1)	60	1.509	4.809	0	0	0.0416	0.4066	32.57
Subsq. damage [1; 1.5)	56	1.733	4.706	0	0	0.0090	0.1937	21.90
Subsq. damage [1.5; 2)	56	0.0983	0.2404	0	0	0	0.1034	1.574
Subsq. damage [2; 3)	49	0.8819	3.126	0	0.0862	0.1713	0.4981	21.42
Prev. damage [0.5; 0)	60	2.106	4.780	0	0	0.1542	1.097	16.28
Prev. damage [1; 0.5)	60	1.463	5.593	0	0	0.1129	0.3137	30.23
Prev. damage [1.5; 1)	60	1.203	5.450	0	0.0045	0.1033	0.1775	30.23
Prev. damage [2; 1.5)	60	0.1686	0.7017	0	0	0.0036	0.0692	5.140
Prev. damage [3; 2)	60	0.7600	1.547	0	0	0.1694	0.4497	5.617
Claims (millions)	60	0.4837	0.4781	0.0180	0.0870	0.2720	0.6931	1.385
GDP change (in %)	60	-2.752	5.562	-20.74	-6.337	-2.836	-0.2744	6.295
Est. (thousands)	60	19.92	17.76	0.0500	8.542	11.77	26.75	67.13
Wage change (in %)	60	11.33	10.85	0.2013	5.475	8.072	10.12	50.98
Mapping distance (km)	60	6.409	15.30	0	0	0	0	80.35

same both for large and extreme catastrophes points to the corollary that high Demand Surge effects correspond to high damages.

Table 4.7: Summary Statistics – Demand Surge.

The table shows descriptive statistics of the average and maximum Demand Surge effect for different time periods after the catastrophes. In Panel A, data for the set of catastrophes with damage of at least 100 million US-$ is reported, Panel B refers to observations with damage of at least 500 million US-$.

	Obs.	Mean	Std. Dev.	Min.	q25	q50	q75	Max.
Panel A: Large catastrophes (damage $\geq$ 100 million US-$)								
Avg. Dem. Surge: 1 year	192	1.268	4.180	-3.283	-0.5101	0.1513	1.129	31.46
Avg. Dem. Surge: 2 years	180	1.562	5.288	-5.528	-0.8582	0.2922	1.758	36.50
Avg. Dem. Surge: 3 years	156	2.018	6.220	-6.663	-0.8331	0.6735	2.671	37.91
Max. Dem. Surge: 2 years	180	3.529	6.517	0	0.0678	1.495	4.225	44.31
Panel B: Extreme catastrophes (damage $\geq$ 500 million US-$)								
Avg. Dem. Surge: 1 year	60	3.294	6.728	-1.328	-0.3928	0.4604	4.044	31.46
Avg. Dem. Surge: 2 years	56	3.932	8.339	-1.928	-0.7958	0.9425	4.437	36.50
Avg. Dem. Surge: 3 years	49	4.679	9.578	-3.066	-0.5353	1.390	4.853	37.91
Max. Dem. Surge: 2 years	56	6.322	10.14	0	0.2219	2.502	6.033	44.31

In addition, Figure 4.2 displays the boxplot of the average Demand Surge effect in a two-year period after the catastrophe (our reference period). The left boxplot relates to large catastrophes, whereas the right boxplot relates to extreme catastrophes. The comparison of both boxplots underlies the observation that high Demand Surge effects correspond to high damages. All statistical parameters of the boxplot are shifted upwards if we restrict the observations to extreme catastrophes.

Finally, in Table 4.8 the pairwise correlations between the above-described variables are presented for the full sample of observations. Based on this univariate analysis nearly all of our hypotheses from Section 4.2 can be confirmed. Nevertheless, the correlation coefficients between the average Demand Surge and both the number of establishments in the construction sector and the wage change in the preceding 18 months prior to the catastrophe have the wrong algebraic sign. Nevertheless, both coefficients are close to zero and the wrong algebraic signs might be the consequence of an omitted variable bias. Against this background, we will test our set of hypotheses in a multivariate setting in Section 4.3.2.3.

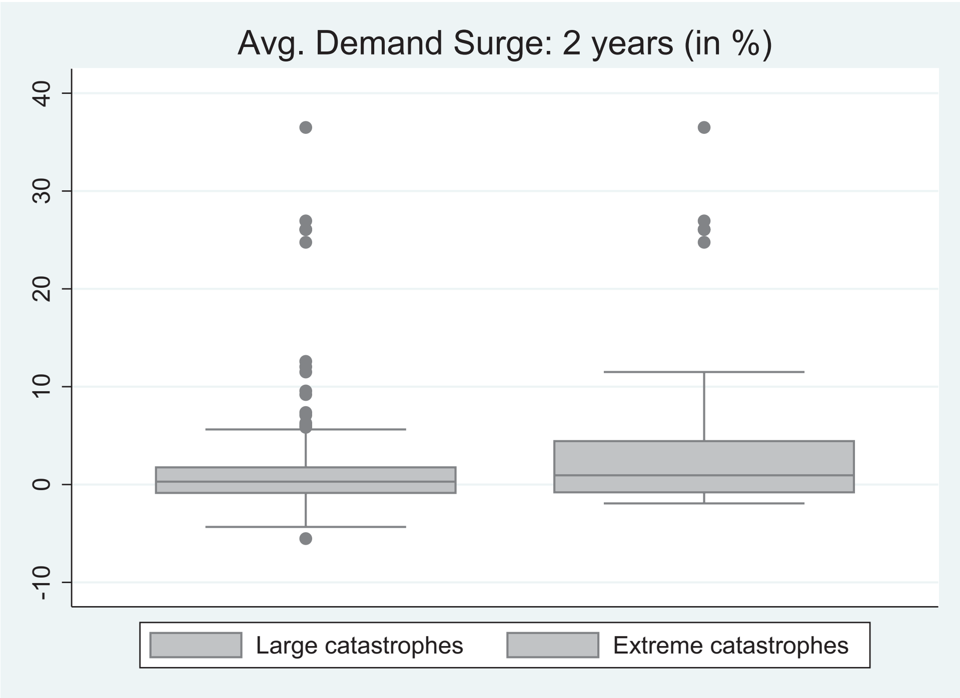

Figure 4.2: Boxplot Average Demand Surge: 2 Years (EM-DAT).

The two boxplots show the distribution of the average Demand Surge effect for a 2-year period after the catastrophe.

Table 4.8: Table of Correlations.

The table presents the pairwise correlations of catastrophe specific and macroeconomic variables.

	Dem. Surge	Damage	Claims	GDP	Est.	Wage	Dist.
Avg. Demand Surge	1.00						
Damage	0.42	1.00					
Claims	0.29	0.47	1.00				
GDP change	0.42	0.17	0.19	1.00			
Establishments	0.05	-0.07	-0.04	0.01	1.00		
Wage change	0.06	0.37	0.34	0.38	-0.02	1.00	
Mapping distance	0.10	0.15	0.10	0.14	-0.33	0.12	1.00

4.3.2.3 Empirical Results

4.3.2.3.1 Demand Surge Effect for Large Catastrophes

Subsequently, we test our hypotheses from Section 4.2, which refer to the impact of catastrophe-specific variables and macroeconomic conditions on Demand Surge. According to Section 4.3.1, we consider catastrophe events with damages of at least 100 million US-$ because it is unlikely that rather small events lead to a significant increase in the demand of building services and, consequently, increasing prices.[89] We analyze the resulting 180 observations using ordinary least squares (OLS) regressions with clustered standard errors, each cluster representing one catastrophe.[90] The results are presented in Table 4.9.

In model (B.1), we test the influence of the damage caused by the catastrophe on Demand Surge.[91] Moreover, we analyze the impact of other catastrophe events that occurring in the same region less than 2 years before or after the considered event. We find that both effects are highly relevant and account for a major share of the variance of Demand Surge, which confirms the damage hypothesis (H1) and the proximity catastrophe hypothesis (H2). To be more specific, the prices of retail labor increase by approximately 2.2 percentage points if damages due to a catastrophe rise by 10 billion US-$. Furthermore, we find that large catastrophes that occur in the same region during the following 1.5 years or the preceding 0.5 years also lead to a significantly higher Demand Surge. In contrast, catastrophes that occurred more than 1.5 years after the considered events do not significantly influence the Demand Surge effect, which indicates that most of the repair work has already been finished when the new event occurs, so the events can be treated as independent when determining the Demand Surge effect. This finding

[89]It would also be interesting to test whether the underlying economic mechanisms differ between different catastrophe types by splitting the data set into different sub-samples for each disaster type specified in Table 4.4. However, due to the small sample size, this is not reasonable and, hence, has to be left for future research.

[90]For a detailed description of cluster-robust standard errors see Appendix 4.5.2.

[91]To the best of our knowledge, the reported damage values in EM-DAT and SHELDUS do not contain Demand Surge effects. Thus, the reported damage coefficients are unbiased and we are not confronted with an endogeneity problem. For a discussion of a potential simultaneity bias in OLS see Wooldridge (2013, p. 534 ff.).

Table 4.9: Demand Surge for Large Catastrophes.

The table reports results of OLS regressions with clustered standard errors regarding influencing factors of Demand Surge. The data set comprises catastrophes with total damage of at least 100 million US-$. Demand Surge is computed as the average increase of the retail labor index in a 2-year period after the catastrophe. The other variables are defined in Table 4.3. We report t-statistics in parentheses. The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	(B.1)	(B.2)	(B.3)	(B.4)
Damage	0.2165***	0.1608***	0.1507***	0.1913***
	(4.30)	(3.87)	(4.04)	(3.74)
Subsq. damage [0; 0.5)	0.1339***	0.1338***	0.1266***	0.1416***
	(7.13)	(7.42)	(7.99)	(7.26)
Subsq. damage [0.5; 1)	0.1941***	0.1832**	0.1636**	0.1549**
	(3.53)	(3.32)	(3.39)	(3.30)
Subsq. damage [1; 1.5)	1.1039***	1.1255***	1.0725***	1.0007***
	(4.71)	(4.84)	(4.72)	(4.50)
Subsq. damage [1.5; 2)	-0.0635	-0.0112	0.0560	0.0153
	(-0.78)	(-0.16)	(1.16)	(0.26)
Prev. damage [0.5; 0)	0.1875†	0.1841†	0.1661†	0.1956*
	(1.92)	(1.96)	(1.88)	(2.29)
Prev. damage [1; 0.5)	-0.0242	-0.0326†	-0.0668*	-0.0098
	(-1.13)	(-1.87)	(-2.04)	(-0.26)
Prev. damage [1.5; 1)	0.0192	0.0017	-0.0859†	0.0390
	(0.59)	(0.05)	(-1.87)	(0.66)
Prev. damage [2; 1.5)	-0.0528	-0.0415	-0.0595	-0.0598
	(-0.70)	(-0.54)	(-0.85)	(-0.87)
Claims		1.4967*	1.3636*	1.5113*
		(2.43)	(2.03)	(2.60)
GDP change			0.2467**	0.2582**
			(3.18)	(3.20)
Establishments			-0.0297†	-0.0265
			(-1.67)	(-1.56)
Wage change				-0.1053†
				(-1.88)
Mapping distance		0.0154†	-0.0012	-0.0001
		(1.70)	(-0.12)	(-0.01)
Constant	-0.3361	-0.7556**	0.8753†	1.6013*
	(-1.24)	(-2.82)	(1.73)	(2.13)
Observations	180	180	180	180
Adjusted R^2	0.730	0.738	0.768	0.772

is generally in line with the insight that catastrophe insurance is short tailed; that is, homeowners' claims after catastrophes are usually paid quite promptly.[92]

In model (B.2), we additionally include the number of insurance claims for a catastrophe. We find that a large number of claims lead to a significantly higher Demand

[92]See Harrington (1997).

Surge. At the same time, the coefficient of total damage is reduced slightly because a large number of claims usually come along with high total damage. This relationship is also confirmed by a correlation between total damage and the number of claims of 0.47 (see Table 4.8). However, as both variables are considered in (B.2), the number of claims does not represent the amount of damage; rather, the positive coefficient indicates that there is a higher chance that insurance claims are settled by insurers if the total number of claims is high. The underlying reason could be a less thorough investigation of claims by insurers due to limited resources. An alternative reason is that there could be high pressure on insurers to quickly settle claims as a result of politics and the media. Either way, our insurance hypothesis (H3) is confirmed.[93] Moreover, we include the variable Mapping distance to consider that, in some cases, the measured price increase might underestimate the actual price increase because macroeconomic data are not available for the exact catastrophe location. However, the variable is only weakly significant with a coefficient close to zero, showing that mapping seems to be appropriate.

When we integrate macroeconomic variables in model (B.3), the effects of damage and number of claims remain basically unchanged. We find that an increase of the GDP in the construction sector in the previous year significantly contributes to Demand Surge. The effect is not only statistically significant, with $p<1\%$, but the economic effect is also substantial: If the GDP increases by 1% before a catastrophe, the resulting Demand Surge effect increases by approximately 0.25 percentage points. This finding confirms the growth hypothesis (H4), which states that Demand Surge is more pronounced if the construction sector is in a stage of growth and there is only little idle capacity. Moreover, if the number of establishments in the construction sector is high, we find that the Demand Surge effect is significantly smaller, which confirms the contractor hypothesis (H5). The rationale behind this result is that in such a situation, capacity adjustments can be performed quickly.

[93] It has to be noted that data provided by PCS regarding the number of insurance claims of natural catastrophes is not available for flood events. During the last decades the National Flood Insurance Program (NFIP) offered premiums below the rate private companies would offer. As a consequence, risks due to major floods are exclusively insured by state programs. Thus, private data provider, like PCS, are not capable of providing claims data regarding flood events. However, we excluded all events for which no insurance data are available to control for this effect.

In Section 4.2 we argued that there can be several reasons for saturation effects for Demand Surge. To test the saturation hypothesis (H6), we analyze if a wage increase for building services in a preceding period of 18 months reduces the Demand Surge effect. We find that the coefficient is indeed significantly negative.

In summary, most effects are very stable in terms of statistical significance and absolute size. Our results suggest that hypotheses H1–H6 are true. Nonetheless, the effects of a cost increase of building services in the period before a catastrophe and the number of establishments in the construction sector are only weakly significant. However, it may be possible that saturation and capacity effects are only relevant for even more severe catastrophe events. Furthermore, the adjusted R^2 of up to 0.772 shows that Demand Surge can, to a large extent, be attributed to the considered effects.

4.3.2.3.2 Demand Surge Effect for Extreme Catastrophes

As stated above, it is reasonable to assume that the Demand Surge effect is only relevant for large catastrophe events; thus, we only considered catastrophes with damages of at least 100 million US-$. Nevertheless, this restriction is somewhat arbitrary, and, ex ante, it is unclear which barrier might be appropriate. To study the above-observed effects further, we subsequently constrain the data set to events with damages of at least 500 million US-$. Due to the higher bound, the number of observations substantially decreases from 180 to 56. The consequence is a low number of degrees of freedom, which can easily lead to the problem of overfitting the data.[94] To reduce this problem, we subsequently use a reduced number of explanatory variables. To be more specific, we consider only variables where we found significant effects on the larger data set.

The regression results for the subsample of extreme events are presented in Table 4.10. The first column is a repetition of model (B.4) to allow easier comparison of the results. Model (C.2) presents regression results for the full sample using a reduced number of explanatory variables to reduce overfitting the data. We find that the reduction of the number of variables leads to a slightly increased adjusted R^2 of 0.778, instead of 0.772.

[94] See Wooldridge (2013).

In model (C.3), we restrict the data set to the subsample of events with damages of at least 500 million US-$. We find that almost all of the considered variables remain statistically significant for the subsample of extreme events. Moreover, the coefficients of most of the considered variables have magnitudes similar to those for the larger data set. Thus, we find that even if the magnitude of Demand Surge is higher for extreme catastrophes, it seems that the cause-and-effect relationship is not very different from the findings based on the data set that includes smaller catastrophes. However, in contrast to the analyses of smaller catastrophes, we find that Wage change is highly significant, with $p<1\%$. Concretely, a cost increase of building services in the preceding 18 months of 10% dampens the Demand Surge effect by 1.5 percentage points. Thus, for extreme catastrophes, saturation effects cause that Demand Surge to indeed be less pronounced, which ultimately confirms the saturation hypothesis (H6). The same observation holds true for the variable Establishments. A ceteris paribus larger number of establishments in the construction sector dampens the Demand Surge effect significantly which confirms the contractor hypothesis (H5).

In summary, for extreme catastrophes with damages of at least 500 million US-$, hypotheses H1-H3, H5, and H6 can be confirmed. Only the growth hypothesis (H4) cannot be confirmed. However, because the coefficient of the variable GDP change is high and similar in magnitude compared to the previous models (where it was highly statistically and economically significant), it should not be concluded that preceding GDP growth in the construction sector has no economically relevant effect because the insignificant result could simply be a consequence of the small data set. Moreover, the adjusted R^2 of 0.874 suggests that, even if the set of explanatory variables is significantly reduced, Demand Surge can largely be explained by the considered economic effects.

Table 4.10: Demand Surge for Extreme Catastrophes.

The table reports results of OLS regressions with clustered standard errors regarding influencing factors of Demand Surge. The data set comprises catastrophes with total damage of at least 500 million US-$. Demand Surge is computed as the average increase of the retail labor index in a 2-year period after the catastrophe. The other variables are defined in Table 4.3. We report t-statistics in parentheses. The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	Damage ≥ 100 million US-$		Damage ≥ 500 million US-$
	(C.1)	(C.2)	(C.3)
Damage	0.1913***	0.1874***	0.0947*
	(3.74)	(3.92)	(2.64)
Subsq. damage [0; 0.5)	0.1416***	0.1384***	0.5337**
	(7.26)	(8.08)	(3.63)
Subsq. damage [0.5; 1)	0.1549**	0.1565**	0.2242*
	(3.30)	(3.35)	(2.74)
Subsq. damage [1; 1.5)	1.0007***	1.0087***	0.7490***
	(4.50)	(4.59)	(4.07)
Subsq. damage [1.5; 2)	0.0153		
	(0.26)		
Prev. damage [0.5; 0)	0.1956*	0.1954*	0.5070***
	(2.29)	(2.23)	(3.69)
Prev. damage [1; 0.5)	-0.0098		
	(-0.26)		
Prev. damage [1.5; 1)	0.0390		
	(0.66)		
Prev. damage [2; 1.5)	-0.0598		
	(-0.87)		
Claims	1.5113*	1.5189*	2.6256***
	(2.60)	(2.65)	(4.38)
GDP change	0.2582**	0.2556**	0.1961
	(3.20)	(3.28)	(1.46)
Establishments	-0.0265	-0.0282†	-0.0812**
	(-1.56)	(-1.97)	(-3.06)
Wage change	-0.1053†	-0.0932*	-0.1534**
	(-1.88)	(-2.31)	(-2.91)
Mapping distance	-0.0001		
	(-0.01)		
Constant	1.6013*	1.5100*	2.0701†
	(2.13)	(2.35)	(1.84)
Observations	180	180	56
Adjusted R^2	0.772	0.778	0.874

4.3.2.3.3 Robustness Checks

Average Demand Surge Effect within Differing Time Periods

In Sections 4.3.2.3.1 and 4.3.2.3.2, we analyzed the effect of several influencing factors on the average Demand Surge after large and extreme catastrophes during the subsequent 2-year period. Even if this period is to some extent arbitrary, we believe that it should be appropriate. Our regression results show that other catastrophes that occur more than 1.5 years after or before the considered catastrophe have no significant effect on Demand Surge. Moreover, the general finding about catastrophe insurance is that claims are usually paid quite promptly.[95] However, as a robustness check, we additionally analyze the average Demand Surge within a 3-year period after the event. Gron (1994) finds that during such a period, approximately 95% of homeowners' claims are paid. Moreover, we examine whether the results change if we consider only one year after the catastrophe.

The results regarding the average Demand Surge effect during the 3-year period are presented in Table 4.11. Because one additional year of data is required to calculate the dependent variable, we cannot compute the Demand Surge for catastrophes at the end of our observation period. As consequence, the number of observations is only 156 if we consider all events with damages of at least 100 million US-$ (instead of 180 observations for the 2-year period). Models (D.1), (D.2), and (D.3) contain the results for catastrophes with damages of at least 100 million US-$; model (D.4) refers to the subset of extreme catastrophes with damages of at least 500 million US-$. We find that the results are very similar to those of Sections 4.3.2.3.1 and 4.3.2.3.2, in terms of both statistical significance and the magnitude of the effects. According to the procedure in Section 4.3.2.3.2, we restrict our set of explanatory variables in model (D.3) to variables where we found significant effects on the full model (D.2). Moreover, we include the variable Establishments as we already noticed in Section 4.3.2.3.2 that the effect of the capacity of the construction sector on Demand Surge seems to be especially important for extreme catastrophes. This observation can be confirmed for the 3-year time period, too. The adjusted R^2 values of these models are even slightly higher compared to the analyses in

[95] See Harrington (1997).

Sections 4.3.2.3.1 and 4.3.2.3.2, with values of 0.792 instead of 0.772 for the larger sample and 0.897 instead of 0.874 if the data set is constrained to extreme catastrophes.

Table 4.11: Robustness Check – Demand Surge in a 3-year Period.

The table reports results of OLS regressions with clustered standard errors regarding influencing factors of the average Demand Surge effect in a period of 3 years after the catastrophe. Models (D.1), (D.2), and (D.3) refer to catastrophes with total damage of at least 100 million US-\$, whereas the relevant barrier for Model (D.4) is 500 million US-\$. The other variables are defined in Table 4.3. We report t-statistics in parentheses. The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	Damage ≥ 100 million US-\$			Damage ≥ 500 million US-\$
	(D.1)	(D.2)	(D.3)	(D.4)
Damage	0.2041***	0.1968***	0.1946***	0.1195**
	(4.87)	(4.43)	(4.89)	(3.36)
Subsq. damage [0; 0.5)	0.1568***	0.1653***	0.1610***	0.5023**
	(8.75)	(9.49)	(11.86)	(2.95)
Subsq. damage [0.5; 1)	0.2285***	0.1831***	0.1859***	0.2166*
	(3.93)	(3.88)	(4.04)	(2.69)
Subsq. damage [1; 1.5)	1.2446***	1.0635***	1.0763***	0.8124***
	(4.76)	(4.31)	(4.45)	(3.87)
Subsq. damage [1.5; 2)	-0.1538	0.0234		
	(-1.23)	(0.25)		
Subsq. damage [2; 3)	0.0757***	0.0578*	0.0609*	0.1342*
	(6.10)	(2.28)	(2.51)	(2.81)
Prev. damage [0.5; 0)	0.2136†	0.2216*	0.2252*	0.5911**
	(1.71)	(2.08)	(2.09)	(3.34)
Prev. damage [1; 0.5)	-0.0315†	-0.0351		
	(-1.73)	(-0.91)		
Prev. damage [1.5; 1)	0.0124	0.0215		
	(0.31)	(0.31)		
Prev. damage [2; 1.5)	-0.0479	-0.0675		
	(-0.59)	(-0.95)		
Prev. damage [3; 2)	-0.0098	-0.0190		
	(-0.28)	(-1.35)		
Claims		1.2714*	1.2702*	1.9983**
		(2.38)	(2.43)	(2.83)
GDP change		0.4009***	0.3827***	0.3181*
		(4.54)	(4.44)	(2.18)
Establishments		-0.0247	-0.0247	-0.0757*
		(-1.28)	(-1.51)	(-2.43)
Wage change		-0.1329†	-0.1302**	-0.1880**
		(-1.95)	(-2.85)	(-3.47)
Mapping distance		-0.0093		
		(-0.60)		
Constant	-0.4331	2.3583*	2.1519*	2.7515†
	(-1.37)	(2.31)	(2.66)	(2.05)
Observations	156	156	156	49
Adjusted R^2	0.742	0.792	0.798	0.897

Similarly, we present the results regarding a 1-year period for the average Demand Surge effect in Table 4.12. Because the required observation period is shorter, we have 192 available observations instead of 180. We find that most of the results are similar to the previous findings. However, the adjusted R^2 is remarkably smaller compared to the previous analyses. This result suggests that it might be more appropriate to measure the economic Demand Surge effect on the basis of a longer horizon, which could also be concluded from McCarty and Smith (2005), who find that, one year after the 2004 hurricane season, only 35% of the damaged buildings were repaired in full and 21% of the repair work had not even started.

Table 4.12: Robustness Check – Demand Surge in a 1-year Period.

The table reports results of OLS regressions with clustered standard errors regarding influencing factors of the average Demand Surge effect in a period of 1 year after the catastrophe. Models (E.1), (E.2), and (E.3) refer to catastrophes with total damage of at least 100 million US-\$, whereas the relevant barrier for Model (E.4) is 500 million US-\$. The other variables are defined in Table 4.3. We report t-statistics in parentheses. The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	Damage ≥ 100 million US-\$			Damage ≥ 500 million US-\$
	(E.1)	(E.2)	(E.3)	(E.4)
Damage	0.2846*	0.3124*	0.3148*	0.1438*
	(2.17)	(2.59)	(2.63)	(2.31)
Subsq. damage [0; 0.5)	0.1176*	0.1297**	0.1301**	0.6520***
	(2.12)	(3.28)	(3.34)	(3.99)
Subsq. damage [0.5; 1)	0.2336*	0.1528*	0.1523*	0.1308
	(2.19)	(2.14)	(2.13)	(1.56)
Prev. damage [0.5; 0)	0.2745	0.2968†	0.2978†	0.6374***
	(1.40)	(1.90)	(1.93)	(4.76)
Prev. damage [1; 0.5)	-0.0550†	-0.0137		
	(-1.67)	(-0.31)		
Claims		1.3821***	1.3840***	2.5341***
		(3.56)	(3.52)	(4.35)
GDP change		0.3102***	0.3106***	0.2681**
		(3.45)	(3.47)	(2.75)
Establishments		0.0177	0.0157	-0.0476
		(0.92)	(0.90)	(-1.69)
Wage change		-0.2319**	-0.2349**	-0.2882***
		(-2.97)	(-3.22)	(-5.30)
Mapping distance		0.0042		
		(0.36)		
Constant	0.1349	2.5353*	2.6033**	3.5057**
	(0.68)	(2.63)	(2.87)	(3.61)
Observations	192	192	192	60
Adjusted R^2	0.422	0.572	0.576	0.796

Maximum Instead of Average Demand Surge Effect

As described in Section 4.3.1, we measure Demand Surge as the average price increase of building services after a catastrophe, e.g., within 2 years. However, actual payments for repair work are not equally distributed in this period, as we assumed in equation 4.2. Nevertheless, in this case it was possible to derive a closed form solution for the computation of the total claim settlement costs in case of a natural disaster. Thus, in addition to the consideration of the average price increase above, it is also reasonable to assume that more repair work is performed when the price of building services is at the maximum level because the high demand causes the price increase. Thus, relying on the average Demand Surge leads to an underestimation of the total costs. Against this background, we alternatively compute the maximum Demand Surge effect within 2 years following a catastrophe. However, because the entirety of repair work is not actually performed during the maximum Demand Surge, this leads to an overestimation of the increase in total costs.

The results regarding the maximum Demand Surge effect are presented in Table 4.13. We find that the results are not substantially different from the analyses of the average Demand Surge effect in Sections 4.3.2.3.1 and 4.3.2.3.2, apart from the fact that the magnitude of Demand Surge is larger, which is a direct result of the different definition of the dependent variable. Furthermore, the coefficients of determination are comparable to the respective analyses of the average Demand Surge. The damage of the catastrophe and the damage of previous and subsequent catastrophes in nearby locations still account for the major share of the variance of Demand Surge. Moreover, a larger number of establishments in the construction sector leads to a less pronounced Demand Surge, whereas a larger number of claims per event increases the Demand Surge effect. Thus, hypotheses H1–H3, and H5 are supported by the results for the maximum Demand Surge effect. As in the analyses of the average Demand Surge effect, the effect of preceding GDP growth for the construction sector is only statistically significant if we analyze the larger data set (models (F.2) and (F.3)). The same observation holds true for the influence of preceding wage increases prior to the occurrence of the catastrophe. However, the coefficients of all variables have the expected sign, and the magnitude of the coefficients is economically plausible and similar to the previous analyses, even in the cases where the coefficients are not statistically significant. Thus, it is quite possible that hypotheses H4 and H6 cannot be confirmed only because the data set is not sufficiently large. Hence, these hypotheses should be re-tested if more data are available to achieve greater clarity.

Table 4.13: Robustness Check – Maximum Demand Surge.

The table reports results of OLS regressions with clustered standard errors regarding influencing factors of the maximum Demand Surge effect in a period of 2 years after the catastrophe. Models (F.1), (F.2), and (F.3) refer to catastrophes with total damage of at least 100 million US-$, whereas the relevant barrier for model (F.4) is 500 million US-$. The other variables are defined in Table 4.3. We report t-statistics in parentheses. The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	Damage $\geq$ 100 million US-$			Damage $\geq$ 500 million US-$
	(F.1)	(F.2)	(F.3)	(F.4)
Damage	0.2350***	0.2303***	0.2333***	0.0962
	(4.44)	(3.67)	(3.73)	(1.61)
Subsq. damage [0; 0.5)	0.2065***	0.2219***	0.2238***	0.7205**
	(11.43)	(11.08)	(11.00)	(3.00)
Subsq. damage [0.5; 1)	0.2642***	0.2177***	0.2170***	0.2442*
	(4.20)	(4.10)	(4.07)	(2.51)
Subsq. damage [1; 1.5)	1.3354***	1.1945***	1.1936***	0.9804***
	(4.53)	(4.36)	(4.36)	(4.17)
Subsq. damage [1.5; 2)	-0.0381	0.0262		
	(-0.52)	(0.29)		
Prev. damage [0.5; 0)	0.2030†	0.2302*	0.2310*	0.5866**
	(1.70)	(2.21)	(2.25)	(3.64)
Prev. damage [1; 0.5)	-0.0634**	-0.0048		
	(-2.89)	(-0.10)		
Prev. damage [1.5; 1)	0.1444***	0.2428**	0.2466***	0.1947
	(3.68)	(2.99)	(3.82)	(1.03)
Prev. damage [2; 1.5)	-0.0586	-0.0656		
	(-0.78)	(-0.96)		
Claims		1.6637**	1.6963**	2.7724**
		(3.31)	(3.42)	(3.41)
GDP change		0.2704**	0.2701**	0.1668
		(3.09)	(3.14)	(1.09)
Establishments		-0.0294	-0.0321†	-0.1241**
		(-1.47)	(-1.75)	(-3.45)
Wage change		-0.1762*	-0.1778**	-0.2050
		(-2.37)	(-2.84)	(-1.52)
Mapping distance		0.0087		
		(0.66)		
Constant	1.1528***	3.6336***	3.7010***	4.5498**
	(3.86)	(3.94)	(4.39)	(3.09)
Observations	180	180	180	56
Adjusted R^2	0.739	0.776	0.780	0.866

4.3.3 SHELDUS Catastrophe Database

SHELDUS contains all natural catastrophes in the United States since 1960 that caused at least one fatality and/or any economic damage.[96] The main data sources are the National Climatic Data Center (Storm Data and Unusual Weather Phenomena), the National Geophysical Data Center, and the Storm Prediction Center. All damage values therein are expressed in US-$ at the time the events took place (current value) and are converted into 2005 US-$ using the United States' CPI to allow a comparison of the values. Moreover, all these values refer to direct damage. To exclude conceivably non-catastrophic events we use again a cut-off value of 100 million US-$ and 500 million US-$, respectively.

4.3.3.1 Demand Surge Drivers

For the direct damage caused by catastrophes, we rely on data from the SHELDUS database. These damages are reported on a county-level. Since different counties in SHELDUS regarding the same event may be mapped to the same Xactware localization, a reassessment algorithm combines these single entries. As a consequence, the direct damage has to be recalculated and is now the sum of the direct damages already calculated. Finally, our damage variable for the upcoming empirical analysis is defined as the sum of the direct damages in the localization specified by Xactware and direct damages in a given radius of 450 km around this localization. The radius of 450 km is chosen in accordance with Section 4.3.2.1 for reasons of comparability. Against this background, we assume that the capacity of the construction sector in the catastrophe area can be represented by the number of establishments/employees within a radius of 450 km.

For information regarding insured property losses, we again use data from PCS. For this purpose we map each entry in PCS to the corresponding entries in SHELDUS. Estimated insurance payments and number of claims in different lines of business, e.g., commercial

[96] Between 1993 and 1995, SHELDUS contains only events with at least one fatality or a property or crop damage of a minimum 50,000 US-$.

and personal, are allocated to each SHELDUS observation according to their relative share of property damage.

To control for the effect of alternative catastrophes in the same region that occurred in temporal proximity, we calculate direct damages in a given radius of 450 km around each catastrophe region for different time intervals. We consider catastrophes up to 3 years before or after the end date of each catastrophe, depending on the chosen value of T. The final sample of catastrophe events spans the time period 2002-2010 as Xactware offers labor price data for all contained localizations since 2002 only.

All other variables of interest, i.e., GDP change, Establishments, and Wage change, are defined in compliance with the procedure described in Section 4.3.2.1. An overview of the set of explanatory variables used in the upcoming empirical analysis is shown in Table 4.14.

Table 4.14: Variable Definitions.

Variable	Definition
Damage	Direct damage of the catastrophe event (in billion US-$).
Subsq. damage (a; b]	Direct damage of subsequent catastrophes in the same region that occurred in temporal proximity (in billion US-$); (a; b] denominates the time period in years with respect to the considered event.
Prev. damage [a; b)	Direct damage of previous catastrophes in the same region that occurred in temporal proximity (in billion US-$); [a; b) denominates the time period in years with respect to the considered event.
Claims	Number of insurance claims (in thousands).
GDP change	Real GDP growth of the construction sector in the affected state.
Establishments	Number of establishments of the construction industry in the affected county/MSA (in thousands).
Wage change	Relative change of wage in the construction sector during the 18 months before the catastrophe.
Mapping distance	Distance between the catastrophe (data from SHELDUS) and the assigned localization of economic variables (data from Xactware) (in km).

4.3.3.2 Descriptive Statistics

Summary statistics of our sample are presented in Tables 4.15 to 4.19. First, we show the distribution of the observations over the full time period of our sample (2002-2010) along with the type of catastrophe in Table 4.15. Again, the number of observations is quite uniformly distributed across the years, with a slightly higher number of events in 2008. As already noted, total losses during this year were quite moderate, but the number of events was the highest since 1998.[97] As can be seen in Panel B, almost all observations result from storms, such as hurricanes, or from floods.

Table 4.15: Summary Statistics – Composition of the Data Set.

	Observations	Percentage
Panel A: Year		
2002	416	8.37
2003	688	13.84
2004	566	11.38
2005	504	10.14
2006	627	12.61
2007	462	9.29
2008	797	16.03
2009	371	7.46
2010	541	10.88
Panel B: Type of Disaster		
Flood	1,084	21.80
Storm	3,825	76.93
Wildfire	31	0.62
Others	32	0.64

In Table 4.16, we present details about the distribution of our set of exogenous variables for the full sample. After excluding all observations with damages of less than 100 million US-$ in the considered region, 4,972 of the total number of 45,185 entries remain. The distribution of the damage is highly right skewed. We observe a mean value of 1.312 billion US-$, a median of 0.2462 billion US-$, and a maximum of 72.41 billion US-$. For the calculation of subsequent and previous damages within a radius of 450 km, we

[97] See Insurance Information Institute (2009).

choose time intervals of half a year up to 2 years before or after the catastrophe and a one-year interval for the remaining time window of up to 3 years. This procedure is in line with the practice of Section 4.3.2.2. For nearly all observations, additional previous or subsequent catastrophes can be observed in the same region. The lower number of observations for subsequent damages in the time window two to three years after the catastrophes is due to limited data availability. Since our data set of catastrophes in the United States ends in 2012 we are not able to calculate subsequent damages resulting from alternative events for observations that end in 2010. Thus, our data set is reduced to 4,431 observations. Furthermore, we find that the GDP change is negative in more than 75% of the cases. Thus, the construction sector most likely had idle capacities at the time the catastrophes took place. A maximum wage change of 52.70% during the previous 18 months corresponds to Hurricane Wilma in Melbourne (Florida) in October 2005. In this case, the foregoing 18 months include the landfalls of Hurricanes Charley, Frances, and Jeanne in Florida, so it is likely that the current wage level was driven strongly by Demand Surge from previous events. We observe that the mean Mapping distance is 45.76 km, which shows that the difference between the location of the catastrophe and the location of the allocated economic data is rather small. In Table 4.17, the number of observations is further reduced. The sample now comprises 1,348 catastrophe events, with minimum sustained damages of 500 million US-\$. As a consequence, the mean value of the damage variable is significantly higher at 4.269 billion US-\$ compared to Table 4.16. The same observation is true for the number of claims. The distributions of all other exogenous variables will not be further discussed since the changes are only marginal.

In Table 4.18, summary statistics are presented for each measure of Demand Surge, both for large (damage $\geq$ 100 million US-\$ in the considered region) and extreme catastrophe events (damage $\geq$ 500 million US-\$ in the considered region). Obviously, the maximum Demand Surge effect is larger than the average Demand Surge effect for the two-year time period. In compliance with the distribution of our damage variable the distribution of each Demand Surge measure is right skewed, too. For large events, the mean Demand Surge effect varies between 0.69% and 1.05%, whereas for extreme catastrophes the mean Demand Surge effect is more pronounced, varying between 2.46% and

Table 4.16: Summary Statistics – Demand Surge Drivers (Damage $\geq$ 100 million US-\$).

The sample comprises 4,972 catastrophe events with a minimum damage of 100 million US-\$. The table shows descriptive statistics of the set of independent variables, which is defined in Table 4.14.

	Obs.	Mean	Std. Dev.	Min.	q25	q50	q75	Max.
Damage (billion US-\$)	4,972	1.312	5.773	0.1000	0.1453	0.2462	0.6294	72.41
Subsq. damage (0; 0.5]	4,972	1.330	6.669	0.0006	0.0868	0.2015	0.6257	78.82
Subsq. damage (0.5; 1]	4,972	1.046	5.314	0.0008	0.0766	0.2101	0.5462	74.28
Subsq. damage (1; 1.5]	4,972	0.8803	2.054	0	0.0810	0.2574	0.6662	52.19
Subsq. damage (1.5; 2]	4,972	0.6206	1.455	0.0006	0.0755	0.1783	0.4602	10.27
Subsq. damage (2; 3]	4,431	3.489	12.05	0.0029	0.3630	0.7374	1.558	80.70
Prev. damage [0.5; 0)	4,972	1.037	5.765	0.0004	0.0747	0.1830	0.4648	74.32
Prev. damage [1; 0.5)	4,972	0.9166	3.928	0.0004	0.0819	0.2288	0.4719	80.46
Prev. damage [1.5; 1)	4,972	0.7195	3.729	0.0002	0.0855	0.2027	0.5159	78.78
Prev. damage [2; 1.5)	4,972	0.6222	3.213	0.0000	0.0766	0.2044	0.4519	75.99
Prev. damage [3; 2)	4,972	1.737	6.295	0.0003	0.2591	0.4981	1.184	80.53
Claims (thousands)	4,972	2.060	13.38	0	0	0.0010	0.1840	372.6
GDP change (in %)	4,972	-4.576	5.535	-25.31	-7.660	-4.334	-1.099	12.21
Establishments (thousands)	4,856	1.920	4.312	0.0300	0.2660	0.6370	1.677	47.56
Wage change (in %)	4,959	7.721	6.270	-6.518	3.923	6.585	10.05	52.70
Mapping distance (km)	4,972	45.76	27.42	0.0001	28.14	42.69	59.66	267.2

Table 4.17: Summary Statistics – Demand Surge Drivers (Damage $\geq$ 500 million US-\$).

The sample comprises 1,348 catastrophe events with a minimum damage of 500 million US-\$. The table shows descriptive statistics of the set of independent variables, which is defined in Table 4.14.

	Obs.	Mean	Std. Dev.	Min.	q25	q50	q75	Max.
Damage (billion US-\$)	1,348	4.269	10.53	0.5031	0.8017	1.546	3.241	72.41
Subsq. damage (0; 0.5]	1,348	3.072	11.92	0.0012	0.0913	0.1727	0.7368	78.78
Subsq. damage (0.5; 1]	1,348	2.284	9.827	0.0018	0.0605	0.2131	0.5535	74.28
Subsq. damage (1; 1.5]	1,348	1.331	3.282	0.0036	0.0709	0.1832	0.4634	52.19
Subsq. damage (1.5; 2]	1,348	0.6331	1.460	0.0006	0.0657	0.1689	0.3674	9.254
Subsq. damage (2; 3]	1,268	4.265	14.20	0.0109	0.3466	0.6508	1.545	80.70
Prev. damage [0.5; 0)	1,348	2.911	10.59	0.0004	0.0984	0.2903	0.9076	74.32
Prev. damage [1; 0.5)	1,348	1.038	2.355	0.0009	0.0540	0.1587	0.4636	16.93
Prev. damage [1.5; 1)	1,348	0.7384	2.156	0.0002	0.0853	0.1977	0.4877	15.75
Prev. damage [2; 1.5)	1,348	0.3368	0.4634	0.0009	0.0477	0.1694	0.5481	9.676
Prev. damage [3; 2)	1,348	1.100	1.562	0.0003	0.2545	0.5197	1.282	16.22
Claims (thousands)	1,348	4.764	23.81	0	0	0	0.3075	372.6
GDP change (in %)	1,348	-3.172	5.334	-20.74	-6.044	-3.099	0.1084	9.265
Establishments (thousands)	1,330	1.668	3.153	0.0500	0.2670	0.6200	1.601	44.70
Wage change (in %)	1,336	9.422	8.072	-4.328	4.542	7.288	10.83	52.70
Mapping distance (km)	1,348	45.19	26.03	0.0001	27.69	42.85	59.79	210.8

3.55%. Again, the maxima remain the same for large and extreme events. This points to the corollary that high Demand Surge effects correspond to high damages as already observed for the EM-DAT database in Section 4.3.2.2.

Table 4.18: Summary Statistics – Demand Surge.

The table shows descriptive statistics of the average and maximum Demand Surge effect for different time periods after the catastrophes. In Panel A, data for the set of catastrophe events with damage of at least 100 million US-$ is reported, Panel B refers to observations with damage of at least 500 million US-$.

	Obs.	Mean	Std. Dev.	Min.	q25	q50	q75	Max.
Panel A: Large catastrophe events (damage $\geq$ 100 million US-$)								
Avg. Dem. Surge: 1 year	4,972	0.6925	3.854	-6.914	-0.8856	-0.1390	0.9475	40.03
Avg. Dem. Surge: 2 years	4,431	0.8647	4.985	-9.557	-1.516	-0.1411	1.645	44.74
Avg. Dem. Surge: 3 years	4,060	1.054	5.789	-11.47	-2.083	-0.0617	2.358	46.14
Max. Dem. Surge: 2 years	4,431	3.452	5.909	0	0	1.500	4.097	50.05
Panel B: Extreme catastrophe events (damage $\geq$ 500 million US-$)								
Avg. Dem. Surge: 1 year	1,348	2.455	6.398	-6.914	-0.7708	0.1627	2.757	40.03
Avg. Dem. Surge: 2 years	1,268	3.114	7.826	-7.998	-0.9125	0.4870	3.967	44.74
Avg. Dem. Surge: 3 years	1,215	3.553	8.631	-8.803	-1.099	0.8963	4.914	46.14
Max. Dem. Surge: 2 years	1,268	6.064	9.253	0	0.3699	2.575	7.386	50.05

Figure 4.3 displays the boxplot of the average Demand Surge effect in a two-year period after the catastrophe (our reference period). We sketch in both the boxplot for large and extreme catastrophes and observe that high Demand Surge effects correspond to high damages. This is apparent from the fact that all statistical parameters of the boxplot are shifted upwards if we restrict the observations to extreme catastrophes.

Ultimately, in Table 4.19 the pairwise correlations between the above-described variables are presented for the full sample of observations. Based on the algebraic signs of the correlation coefficients nearly all of our hypotheses from Section 4.2 can be confirmed. An exemption in this respect is only the wrong algebraic sign of the variable Establishments. Nonetheless, the correlation coefficient is close to zero and the wrong algebraic sign might result from an omitted variable bias. Hence, we will retest our catastrophe specific and macroeconomic hypotheses in a multivariate setting in the following sections.

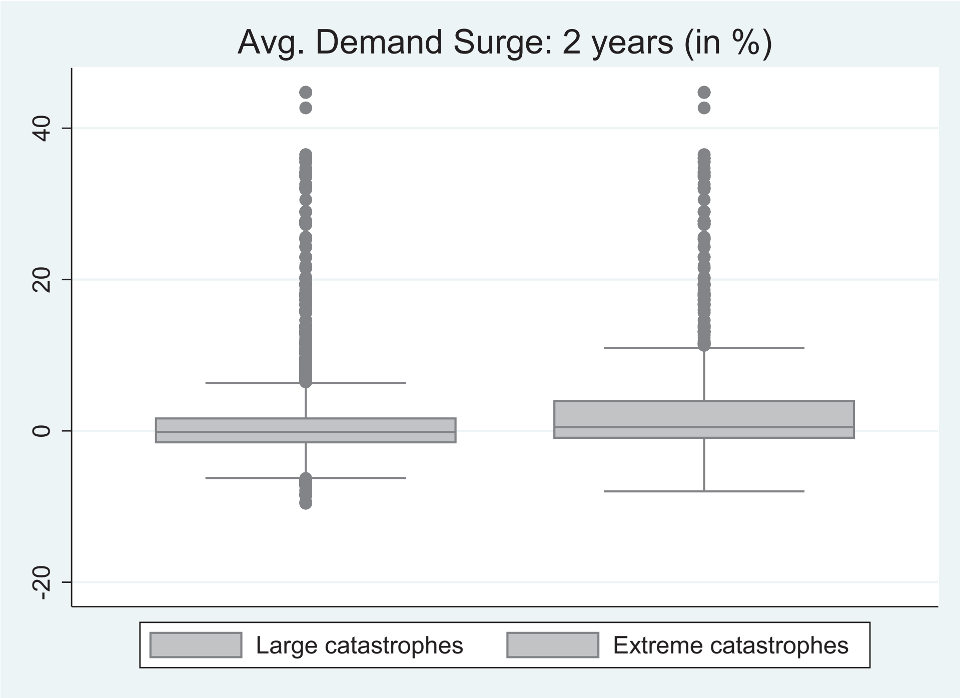

Figure 4.3: Boxplot Average Demand Surge: 2 Years (SHELDUS).

The two boxplots show the distribution of the average Demand Surge effect for a 2-year period after the catastrophe.

Table 4.19: Table of Correlations.

The table presents the pairwise correlations of catastrophe specific and macroeconomic variables.

	Dem. Surge	Damage	Claims	GDP	Est.	Wage	Dist.
Avg. Demand Surge	1.00						
Damage	0.18	1.00					
Claims	0.18	0.28	1.00				
GDP change	0.32	0.09	0.09	1.00			
Establishments	0.04	-0.02	0.05	0.06	1.00		
Wage change	-0.00	0.29	0.12	0.19	0.01	1.00	
Mapping distance	-0.09	-0.02	-0.05	0.02	-0.19	-0.05	1.00

4.3.3.3 Empirical Results

By analogy with Section 4.3.2.3 we replicate the results for the SHELDUS database. To this end, we first examine influencing factors on the average Demand Surge effect for large catastrophes. Afterwards, we restrict our sample to more extreme catastrophes with a direct damage of at least 500 million US-$. In the end, we conduct several robustness checks. We compute the average Demand Surge effect for different time periods of 1 and 3 years, and calculate the maximum instead of the average Demand Surge effect for our reference period of 2 years.

4.3.3.3.1 Demand Surge Effect for Large Catastrophes

This section aims at analyzing the influence of catastrophe-specific variables and macroeconomic conditions on Demand Surge. To this end, we test our set of hypotheses from Section 4.2. Again, we only consider catastrophes with damages of at least 100 million US-$ in the considered region since rather small events normally do not lead to a significant increase in the demand of building services and, consequently, increasing prices. Finally, we analyze the resulting 4,431 observations using OLS regressions. The results regarding the mean Demand Surge effect are presented in Table 4.20.

First, we analyze the influence of the damage caused by the catastrophe together with the impact of other catastrophe events occurring in the same region less than 2 years before or after the considered event on the mean Demand Surge effect in model (A.1). Both effects are highly significant and account for a major share of the variance of Demand Surge. Thus, we can confirm the damage hypothesis (H1) and the proximity catastrophe hypothesis (H2). In concrete terms, the prices of retail labor increase by approximately 1 percentage point if damages due to a catastrophe rise by 10 billion US-$. In addition, catastrophes that occurred more than 0.5 years before or more than 1.5 years after the considered events do not significantly influence the Demand Surge effect. This indicates that most of the repair work has already been finished when the new event occurs, so the events can be treated as independent when determining the Demand Surge effect. This finding confirms the insight that catastrophe insurance is short tailed, too.

Table 4.20: Demand Surge for Large Catastrophes.

The table reports results of OLS regressions regarding influencing factors of the average Demand Surge. The data set comprises catastrophe events with total damage of at least 100 million US-$. Demand Surge is computed as the average increase of the retail labor index in a 2-year period after the catastrophe. The other variables are defined in Table 4.14. We report t-statistics in parentheses. The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	(A.1)	(A.2)	(A.3)	(A.4)
Damage	0.1095***	0.0892***	0.0809***	0.0979***
	(10.87)	(8.58)	(8.02)	(9.55)
Subsq. damage (0; 0.5]	0.0851***	0.0844***	0.0732***	0.0917***
	(9.73)	(9.72)	(8.70)	(10.54)
Subsq. damage (0.5; 1]	0.1865***	0.1818***	0.1720***	0.1673***
	(17.12)	(16.78)	(16.38)	(16.14)
Subsq. damage (1; 1.5]	1.1312***	1.1109***	1.0393***	0.9729***
	(36.90)	(36.32)	(34.47)	(32.24)
Subsq. damage (1.5; 2]	-0.0073	-0.0107	0.0337	0.0097
	(-0.18)	(-0.27)	(0.87)	(0.25)
Prev. damage [0.5; 0)	0.1418***	0.1401***	0.1325***	0.1446***
	(14.12)	(14.05)	(13.72)	(14.96)
Prev. damage [1; 0.5)	-0.0109	-0.0101	-0.0560***	-0.0344*
	(-0.73)	(-0.68)	(-3.85)	(-2.35)
Prev. damage [1.5; 1)	-0.0130	-0.0196	-0.0664***	-0.0466**
	(-0.84)	(-1.08)	(-4.41)	(-3.09)
Prev. damage [2; 1.5)	-0.0195	-0.0273	-0.0373*	-0.0357*
	(-1.07)	(-1.57)	(-2.12)	(-2.06)
Claims		0.0318***	0.0269***	0.0287***
		(6.93)	(6.04)	(6.52)
GDP change			0.2819***	0.2887***
			(19.30)	(19.95)
Establishments			0.0155	0.0166
			(0.97)	(1.05)
Wage change				-0.0791***
				(-6.88)
Mapping distance		-0.0082***	-0.0093***	-0.0108***
		(-2.76)	(-4.17)	(-4.88)
Constant	-0.6070***	-0.2409†	0.9137***	1.6399***
	(-7.81)	(-1.83)	(6.00)	(9.08)
Observations	4,431	4,431	4,318	4,305
Adjusted R^2	0.344	0.353	0.405	0.407

Next, we include the number of insurance claims for a catastrophe in model (A.2). While a large number of claims lead to a significantly higher Demand Surge, the coefficient of total damage is reduced slightly. Often, a large number of claims come along with high total damage. This relationship is also confirmed by a correlation between total damage and the number of claims of 0.28 (see Table 4.19). Nevertheless, the number of claims does not represent the amount of damage as both variables are contained in model

(A.2). Instead, the positive coefficient indicates that there is a higher chance that insurance claims are settled if the total number of claims is high. At this point, we provide two possible explanations. On the one hand, limited resources could lead to a less thorough investigation of claims by insurers. On the other hand, there could be high pressure on insurers to quickly settle claims as a result of politics and the media coverage. Either way, our insurance hypothesis (H3) is confirmed. Furthermore, we include the variable Mapping distance. Hence, we consider that, in some cases, the measured price increase might underestimate the actual price increase because macroeconomic data are not available for the exact catastrophe location. We expect that if the distance between the catastrophe (data from SHELDUS) and the assigned localization of economic variables (data from Xactware) is large, the measured Demand Surge effect should be smaller. The significantly negative coefficient of Mapping distance confirms this expectation.

In model (A.3) we additionally consider macroeconomic variables. We observe that an increase of the GDP in the construction sector during the previous year leads to a significantly higher Demand Surge, which confirms our growth hypothesis (H4). Thus, the Demand Surge effect is indeed more pronounced if the construction sector is in a stage of growth and there is only little idle capacity. Not only is the effect statistically significant, with $p<0.1\%$, but the economic effect is also substantial: If the GDP increases by 1% before a catastrophe, the resulting Demand Surge effect increases by approximately 0.28 percentage points. In contrast, the effect of Establishments is not significant so we cannot confirm our contractor hypothesis (H5). Along the way, the effects of damage and number of claims remain largely unchanged.

According to Section 4.2 there can be several reasons for saturation effects for Demand Surge. To test the saturation hypothesis (H6), we include the variable Wage change in model (A.4), which measures the wage increase for building services in a preceding period of 18 months prior to the catastrophe. We find that the coefficient is negative and statistically highly significant. If wages in the construction sector have already been increased by 10% in the preceding period, the Demand Surge effect is dampened by 0.8 percentage points. Thus, we can confirm the saturation hypothesis (H6).

In summary, most effects are very stable in terms of statistical significance and absolute size. Our results support the hypotheses H1-H4 and H6. Furthermore, the adjusted R^2 of up to 0.407 shows that a major share of the variance of Demand Surge can be explained by the considered economic effects.

4.3.3.3.2 Demand Surge Effect for Extreme Catastrophes

In the preceding section we only considered catastrophe events with damages of at least 100 million US-$ in the considered region since we assumed that Demand Surge effects are only relevant for large catastrophe events. Subsequently and in analogy with Section 4.3.2, we further constrain the data set to events with damages of at least 500 million US-$ to study the above-observed effects further. In so doing we are convinced to provide evidence that our results are universally valid and do not depend on a specific threshold. Due to the higher bound, the number of observations substantially decreases from 4,305 to 1,238. In comparison with Table 4.10, which presents empirical results regarding EM-DAT data, we do not face the problem of overfitting the data due to a low number of degrees of freedom. As a consequence, we do not constrain our model to the set of explanatory variables where we found significant effects for the larger data set.

Table 4.21 contains regression results for the subsample of extreme events. The first column is a repetition of model (A.4) to allow easier comparison of the results. In models (B.2) and (B.3), we restrict the data set to the subsample of events with damages of at least 500 million US-$. We find that almost all of the considered variables remain statistically significant for the subsample of extreme events. In addition, the magnitudes of the coefficients are in most of the cases similar to those for the larger data set. Thus, it seems that the cause-and-effect relationship is not very different from the findings based on the data set that includes smaller catastrophes. One interesting and rather astonishing observation is that in model (B.2), alternative catastrophes that occur 12 to 18 months before the catastrophe seem to dampen the Demand Surge effect. Though, this effect vanishes if we include the variable Wage change in model (B.3). However, both variables may measure a similar effect. Whereas the variable Previous Damage [1.5; 1) controls for the effect of alternative catastrophe events in the time period 12 to 18 months before

Table 4.21: Demand Surge for Extreme Catastrophes.

The table reports results of OLS regressions regarding influencing factors of the average Demand Surge. The data set comprises catastrophe events with total damage of at least 500 million US-$. Demand Surge is computed as the average increase of the retail labor index in a 2-year period after the catastrophe. The other variables are defined in Table 4.14. We report t-statistics in parentheses. The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	Damage ≥ 100 million US-$	Damage ≥ 500 million US-$	
	(B.1)	(B.2)	(B.3)
Damage	0.0979***	0.0929***	0.1309***
	(9.55)	(6.02)	(8.33)
Subsq. damage (0; 0.5]	0.0917***	0.0938***	0.1330***
	(10.54)	(6.59)	(9.09)
Subsq. damage (0.5; 1]	0.1673***	0.1387***	0.1161***
	(16.14)	(9.11)	(7.72)
Subsq. damage (1; 1.5]	0.9729***	0.9745***	0.8778***
	(32.24)	(19.33)	(17.76)
Subsq. damage (1.5; 2]	0.0097	-0.0525	-0.1304
	(0.25)	(-0.51)	(-1.32)
Prev. damage [0.5; 0)	0.1446***	0.1189***	0.1460***
	(14.96)	(8.45)	(10.42)
Prev. damage [1; 0.5)	-0.0344*	-0.5610***	-0.2629**
	(-2.35)	(-6.97)	(-3.00)
Prev. damage [1.5; 1)	-0.0466**	-0.4393***	0.0530
	(-3.09)	(-5.96)	(0.55)
Prev. damage [2; 1.5)	-0.0357*	0.5406	0.5494
	(-2.06)	(0.96)	(1.01)
Claims	0.0287***	0.0212***	0.0220***
	(6.52)	(3.31)	(3.56)
GDP change	0.2887***	0.6540***	0.6554***
	(19.95)	(15.56)	(16.12)
Establishments	0.0166	0.0829†	0.0754
	(1.05)	(1.72)	(1.60)
Wage change	-0.0791***		-0.2517***
	(-6.88)		(-7.56)
Mapping distance	-0.0108***	-0.0202***	-0.0244***
	(-4.88)	(-3.32)	(-4.13)
Constant	1.6399***	3.5496***	5.4069***
	(9.08)	(7.84)	(10.96)
Observations	4,305	1,250	1,238
Adjusted R^2	0.407	0.550	0.569

a catastrophe, Wage change captures the effect of price increases for building services in the foregoing 18 months. However, preceding price increases are often triggered by previous catastrophe events, so that both variables are economically related.

We have two empirical observations suggesting that this is indeed the case. First, we find that the coefficient of Previous Damage [1.5; 1) has a negative sign in model (B.2), which is in contrast to the findings for subsequent damages. This negative sign could be explained by saturation effects, resulting in a restraining effect for previous catastrophes on Demand Surge. Second, we find that the variables Wage change and Previous Damage [1.5; 1) are highly correlated, with a correlation coefficient of 0.53.

We find that a cost increase of building services in the preceding 18 months of 10% dampens the Demand Surge effect by 2.5 percentage points. Thus, saturation effects cause that Demand Surge to indeed be less pronounced, which confirms the saturation hypothesis (H6). Moreover, the economic effect of a previous wage change is much more pronounced compared to the analysis of relatively smaller catastrophe events in Section 4.3.3.3.1. Though, this was to be expected because a saturation effect is most likely for events with very high damages.

In a nutshell, for extreme events with damages of at least 500 million US-$, hypotheses H1-H4 and H6 can be confirmed. Rather astonishing, the effect of the number of establishments on Demand Surge seems to be positive, which contradicts our hypothesis H5 and previous observations regarding EM-DAT data in Section 4.3.2. So far, we have no justification for this observation. Nevertheless, the effect is not significant in the full model (B.3). Again, the adjusted R^2 of 0.569 suggests that Demand Surge can largely be explained by the considered economic effects.

4.3.3.3.3 Robustness Checks

Average Demand Surge Effect within Differing Time Periods

In the previous Sections 4.3.3.3.1 and 4.3.3.3.2, we analyzed the effect of macroeconomic and catastrophe specific factors on the average Demand Surge during the subsequent 2-year period. We are aware of the fact that this period is to some extent arbitrary, but we believe that it should be appropriate. The regression results in Table 4.21 show that other catastrophes that occur more than 1.5 years after or before the considered catastrophe have no significant effect on Demand Surge if we restrict our observations to extreme catastrophes. Nonetheless, we conduct several robustness checks. We additionally analyze the average Demand Surge within a 3-year period after the event and examine whether the results change if we consider only one year after the catastrophe.

We present results regarding the average Demand Surge effect during the 3-year period in Table 4.22. In this case, we need one additional year of data to calculate our dependent variable. As a consequence, we cannot compute the Demand Surge for catastrophes at the end of our observation period, and, thus, the number of observations is reduced to 4,060 if we consider events with damages of at least 100 million US-$ (instead of 4,431 observations for the 2-year period). Models (C.1) and (C.2) contain results for events with damages of at least 100 million US-$; model (C.3) refers to the subset of extreme events with damages of at least 500 million US-$. The results are very similar to those of Sections 4.3.3.3.1 and 4.3.3.3.2, in terms of both statistical significance and the magnitude of the effects. Finally, the adjusted R^2 values of these models are even slightly higher compared to the analyses in Sections 4.3.3.3.1 and 4.3.3.3.2, with values of 0.430 instead of 0.407 for the larger sample and 0.606 instead of 0.569 if the data set is constrained to extreme catastrophes.

Similarly, we present the results for the average Demand Surge effect in a 1-year period after the catastrophe events in Table 4.23. As we compute the average Demand Surge effect for a 1-year period we can make use of our full sample of observations for the time period 2002-2010. Thus, we have 4,972 available observations instead of 4,431. We find that most of the results are similar to the previous findings as well. However, the adjusted R^2 is remarkably smaller compared to the previous analyses. This result suggests that a 1-year time period might be too short to measure the economic Demand Surge effect, and, therefore, confirms our choice of a 2-year time period as our reference.

Table 4.22: Robustness Check – Demand Surge in a 3-year Period.

The table reports results of OLS regressions regarding influencing factors of the average Demand Surge effect in a period of 3 years after the catastrophe. Models (C.1) and (C.2) refer to catastrophe events with total damage of at least 100 million US-\$, whereas the relevant barrier for model (C.3) is 500 million US-\$. The other variables are defined in Table 4.14. We report t-statistics in parentheses. The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	Damage $\geq$ 100 million US-\$		Damage $\geq$ 500 million US-\$
	(C.1)	(C.2)	(C.3)
Damage	0.1099***	0.1006***	0.1382***
	(9.53)	(8.64)	(8.37)
Subsq. damage (0; 0.5]	0.0848***	0.0931***	0.1391***
	(8.47)	(9.42)	(9.05)
Subsq. damage (0.5; 1]	0.2051***	0.1827***	0.1208***
	(16.45)	(15.51)	(7.61)
Subsq. damage (1; 1.5]	1.3722***	1.1615***	1.0128***
	(38.09)	(32.91)	(18.39)
Subsq. damage (1.5; 2]	0.1059†	0.1231*	0.3281*
	(1.96)	(2.40)	(2.21)
Subsq. damage (2; 3]	0.0068	0.0135*	-0.0036
	(1.12)	(2.30)	(-0.31)
Prev. damage [0.5; 0)	0.1376***	0.1417***	0.1515***
	(11.98)	(12.91)	(10.30)
Prev. damage [1; 0.5)	-0.0116	-0.0390*	-0.1831†
	(-0.67)	(-2.31)	(-1.96)
Prev. damage [1.5; 1)	-0.0205	-0.0597***	0.0705
	(-1.16)	(-3.47)	(0.67)
Prev. damage [2; 1.5)	-0.0159	-0.0359†	0.8361
	(-0.76)	(-1.82)	(1.45)
Prev. damage [3; 2)	-0.0155	-0.0275**	-0.3423***
	(-1.46)	(-2.76)	(-3.31)
Claims		0.0268***	0.0215***
		(5.32)	(3.31)
GDP change		0.3495***	0.7624***
		(20.11)	(16.88)
Establishments		0.0049	0.0141
		(0.26)	(0.28)
Wage change		-0.0975***	-0.3104***
		(-7.35)	(-8.70)
Mapping distance		-0.0103***	-0.0224***
		(-3.83)	(-3.49)
Constant	0.7192***	1.9762***	6.4199***
	(-7.62)	(9.18)	(11.54)
Observations	4,060	3,934	1,185
Adjusted R^2	0.365	0.430	0.606

Table 4.23: Robustness Check – Demand Surge in a 1-year Period.

The table reports results of OLS regressions regarding influencing factors of the average Demand Surge effect in a period of 1 year after the catastrophe. Models (D.1) and (D.2) refer to catastrophe events with total damage of at least 100 million US-$, whereas the relevant barrier for model (D.3) is 500 million US-$. The other variables are defined in Table 4.14. We report t-statistics in parentheses. The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	Damage $\geq$ 100 million US-$		Damage $\geq$ 500 million US-$
	(D.1)	(D.2)	(D.3)
Damage	0.0981***	0.0957***	0.1210***
	(11.00)	(10.73)	(8.27)
Subsq. damage (0; 0.5]	0.0711***	0.0908***	0.1255***
	(9.19)	(12.02)	(9.35)
Subsq. damage (0.5; 1]	0.1509***	0.1287***	0.0805***
	(15.72)	(14.26)	(5.82)
Prev. damage [0.5; 0)	0.1480***	0.1534***	0.1483***
	(16.71)	(18.20)	(11.27)
Prev. damage [1; 0.5)	-0.0300*	-0.0248*	-0.3031***
	(-2.27)	(-1.96)	(-4.07)
Claims		0.0319***	0.0245***
		(8.58)	(4.18)
GDP change		0.2008***	0.5812***
		(21.20)	(21.30)
Establishments		0.0246*	0.1069*
		(2.16)	(2.39)
Wage change		-0.1272***	-0.2907***
		(-13.64)	(-12.96)
Mapping distance		-0.0132***	-0.0336***
		(-8.58)	(-6.26)
Constant	0.1855***	2.5687***	7.0484***
	(3.35)	(18.22)	(18.64)
Observations	4,972	4,843	1,318
Adjusted R^2	0.136	0.238	0.411

Maximum Instead of Average Demand Surge Effect

So far we measured Demand Surge as the average price increase of building services after a catastrophe. To this end, we used a reference period of two years. Consequently, we assumed that payments for repair work are equally distributed in this two year period. But even if the concrete distribution is unknown, it is reasonable to assume that more repair work is conducted when the price of building services is at the maximum level. The rationale behind this assumption is that the high demand causes the price increase. Thus, relying on the average Demand Surge leads to an underestimation of total costs. Thus, as another robustness check, we additionally compute the maximum Demand Surge effect within two years following a catastrophe. In this case, we would overestimate the increase in total costs, because the entirety of repair work is not actually performed during the maximum Demand Surge.

Table 4.24 reports the results regarding the maximum Demand Surge effect. Compared to Sections 4.3.3.3.1 and 4.3.3.3.2 we find that the results are not substantially different from the analyses of the average Demand Surge effect. Of course, the magnitude of Demand Surge is larger by definition of the dependent variable. The coefficients of determination are even higher than in the respective analyses of the average Demand Surge. Regarding the influence of the damage of the catastrophe itself and the damage of previous and subsequent catastrophes in nearby locations we find that both effects still account for a major share of the variance of Demand Surge. Furthermore, a preceding wage increase for building services leads to a less pronounced Demand Surge, whereas a larger number of claims per event increase the Demand Surge effect. As in the analyses of the average Demand Surge effect, the effects of preceding GDP growth for the construction sector and of Wage change are particularly pronounced if we restrict the sample to events with damage of at least 500 million US-$. Again, the effect of Establishments on Demand Surge is positive but virtually not significant. To sum up, hypotheses H1-H4 and H6 are also supported by the results for the maximum Demand Surge effect.

Table 4.24: Robustness Check – Maximum Demand Surge.

The table reports results of OLS regressions regarding influencing factors of the maximum Demand Surge effect in a period of 2 years after the catastrophe. Models (E.1) and (E.2) refer to catastrophe events with total damage of at least 100 million US-$, whereas the relevant barrier for model (E.3) is 500 million US-$. The other variables are defined in Table 4.14. We report t-statistics in parentheses. The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	Damage $\geq$ 100 million US-$		Damage $\geq$ 500 million US-$
	(E.1)	(E.2)	(E.3)
Damage	0.1223***	0.1143***	0.1417***
	(10.63)	(9.74)	(7.87)
Subsq. damage (0; 0.5]	0.0986***	0.1107***	0.1485***
	(9.88)	(11.10)	(8.85)
Subsq. damage (0.5; 1]	0.2289***	0.2075***	0.1658***
	(18.40)	(17.47)	(9.63)
Subsq. damage (1; 1.5]	1.5005***	1.3117***	1.2180***
	(42.86)	(37.94)	(21.51)
Subsq. damage (1.5; 2]	-0.0040	0.0064	-0.0813
	(-0.09)	(0.015)	(-0.72)
Prev. damage [0.5; 0)	0.1495***	0.1560***	0.1513***
	(13.05)	(14.08)	(9.43)
Prev. damage [1; 0.5)	-0.0179	-0.0373*	-0.3077**
	(-1.05)	(-2.22)	(-3.07)
Prev. damage [1.5; 1)	-0.0146	-0.0459**	0.0338
	(-0.83)	(-2.66)	(0.31)
Prev. damage [2; 1.5)	-0.0085	-0.0259	-0.0170
	(-0.41)	(-1.31)	(-0.03)
Claims		0.0312***	0.0245***
		(6.20)	(3.47)
GDP change		0.3105***	0.6651***
		(18.73)	(14.27)
Establishments		0.0350†	0.0527
		(1.93)	(0.98)
Wage change		-0.1048***	-0.2574***
		(-7.96)	(-6.75)
Mapping distance		-0.0129***	-0.0287***
		(-5.08)	(-4.25)
Constant	1.6037***	4.2052***	8.1897***
	(18.08)	(20.32)	(14.49)
Observations	4,431	4,305	1,238
Adjusted R^2	0.391	0.444	0.594

4.4 Interim Results

In this chapter, we have proposed an approach to quantifying the Demand Surge effect from an insurer's point of view, and have provided an econometric analysis of the effect. Our econometric model is able to explain a major share of the variance of the Demand

Surge effect and is thereby able to identify the most important determinants of Demand Surge. According to the model, highly relevant drivers of Demand Surge are the amount of loss of a catastrophe and further catastrophes that occur in close proximity in terms of time in the same region. In concrete terms, a damage increase of 10 billion US-$ will lead to a price increase in retail labor of approximately 1 percentage point (SHELDUS) to 1.9 percentage points (EM-DAT). In addition, further catastrophes that occur in the same region within the following 1.5 years or the preceding 0.5 years imply a significantly higher Demand Surge. The model also deduces a significantly positive relationship between the number of settled insurance claims for a catastrophe and the Demand Surge effect. Because a larger number of claims usually results from a higher total damage, the consideration of both variables in the model indicates that the regulation policy of insurers is less restrictive if the total number of claims is high. Furthermore, we see a positive relationship between the GDP of the construction sector and Demand Surge. If the GDP increases by 1% before a catastrophe, we find the Demand Surge effect to rise by approximately 0.26 percentage points (EM-DAT) and 0.29 percentage points (SHELDUS). Consequently, the Demand Surge effect is more pronounced if the construction sector is in a growth stage, which is associated with reduced idle capacity in this sector. Moreover, we find a changing relationship between the number of establishments in the construction sector and Demand Surge. In Section 4.3.2 an increasing number of establishments leads to a less pronounced Demand Surge effect. This might be due to a greater ability to adjust the capacity in the construction sector. Nonetheless, it must be emphasized that this effect is not statistically significant if we consider smaller catastrophes. By contrast, this finding cannot be confirmed in Section 4.3.3. One possible explanation is that the total number of establishments in the construction industry is not a good proxy for its capacity. Implicitly, we assumed one uniform size for each establishment which is not realistic. In addition, we observe a saturation effect according to which a wage increase for building services before a catastrophe leads to a reduced Demand Surge effect. Both in Sections 4.3.2 and 4.3.3, we use a cut-off value of 100 million US-$ and 500 million US-$ for events to be included in the sample. Whereas SHELDUS data are exclusively county-level data, catastrophe regions in EM-DAT are mainly specified on the state-level. Therefore, the insignificant results for smaller catastrophes in the EM-DAT sample might just be a direct result of a less restrictive barrier for events to be entered into the sample. The results for the hypotheses analyzed in this chapter are summarized in Table 4.25.

Table 4.25: Summary of Results.

The table summarizes the hypotheses and results regarding the positive or negative dependence of Demand Surge. Accordingly, the symbols ✓ and ✗ denote the confirmation and refusal of each hypothesis.

Hypothesis	Variable	Expected sign	Result
H1: Damage hypothesis	Damage	+	✓
H2: Proximity cat. hypothesis	Subsequent damage	+	✓
	Previous damage		
H3: Insurance hypothesis	Claims	+	✓
H4: Growth hypothesis	GDP change	+	✓
H5: Contractor hypothesis	Establishments	–	✗
H6: Saturation hypothesis	Wage change	–	✓

These results should have important implications for insurance companies and their investors as well as issuers and investors of catastrophe-linked securities. Insurance companies have to consider the Demand Surge effect within the framework of the calculation of insurance premiums and the determination of economic capital. With respect to the determination of economic capital, it should be noted that, particularly if tail events (like great catastrophes) occur, considering or not considering the Demand Surge effect can be the difference between insolvency and solvency for an insurance company. For investors of insurance companies, estimates of Demand Surge effects are also highly relevant to assess the price reactions of insurance stocks after catastrophes.[98] Ultimately, issuers and investors of catastrophe-linked securities have to determine the risk profile of catastrophe losses and, especially, the price reaction of these securities due to the occurrence of natural catastrophes. Thus, for all of these market participants, the results should be useful for appropriately assessing Demand Surge effects.

[98] For a discussion of the response of insurance stocks after natural catastrophes see Gangopadhyay et al. (2010), Lamb (1995), Marlett et al. (2000), and Shelor et al. (1992).

4.5 Appendix

4.5.1 Mapping Algorithm

As already mentioned in Section 4.3.1 the localizations of catastrophe regions provided by EM-DAT/SHELDUS are usually not consistent with pricing information for the economic areas specified by Xactware. Thus, we mapped each EM-DAT/SHELDUS localization to the closest Xactware localization available. To this end, we used the following mapping algorithm:

1. For each localization in EM-DAT/SHELDUS and Xactware retrieve the corresponding geographic coordinates in WGS 84.

2. For each localization in EM-DAT/SHELDUS calculate the distance to all localizations in Xactware with the following formula (shortest distance of two points A and B on a surface of a sphere):

$$\xi = arccos\left\{sin\left(\phi_A\right) \cdot sin\left(\phi_B\right) + cos\left(\phi_A\right) \cdot cos\left(\phi_B\right) \cdot cos\left(\lambda_B - \lambda_A\right)\right\};$$
$$L = \xi \cdot 6370\ km;$$

   with:

$$\phi_{A,B} = latitude\ of\ point\ A/B;$$
$$\lambda_{A,B} = longitude\ of\ point\ A/B;$$
$$L = distance\ between\ point\ A\ and\ B.$$

3. Map each localization in EM-DAT/SHELDUS to the localization in Xactware with the shortest calculated distance in step 2.

The available information for each mapping are the assigned localization in Xactware and the respective distance in km. The results of the mapping procedure are contained in Tables 4.5 and 4.6 for EM-DAT data and in Tables 4.16 and 4.17 for SHELDUS data.

4.5.2 Cluster-Robust Standard Errors

The data set for the present analysis includes several catastrophe events like, e.g., Hurricane Katrina. Each observation in turn corresponds to a catastrophe region of a catastrophe event. Therefore, it is reasonable to assume that all observations belonging to the same catastrophe event (cluster) are correlated with each other, i.e., we can observe within-cluster correlation. This might be due to a comparable economic situation in all affected regions or federal disaster assistance that is specific to the catastrophe event.[99] Across clusters we still assume independence. As a consequence the Gauss-Markov assumption of independent observations does no longer hold.[100] If standard OLS regression is performed standard errors are underestimated and t-statistics overestimated. Accounting for within-cluster correlation does not change coefficient estimates but leads to cluster- and heteroskedastic-robust standard errors. For this purpose Liang and Zeger (1986) generalize the White (1980) heteroskedastic-robust covariance matrix estimator. For an implementation in Stata see StataCorp LP (2013).

[99] This problem is known in literature as the Moulton problem, who first described the problem of correlated observations in Moulton (1986) and Moulton (1990). A detailed description and comparison of solutions to the Moulton problem can be found in Angrist and Pischke (2009).

[100] For a detailed description of the Gauss-Markov assumptions (for cross-sectional regression) see Wooldridge (2013, p. 79-89).

5 Impact of Natural Disasters on Reconstruction Labor Wages

5.1 Fundamentals and Research Questions

In addition to Chapter 4 we will further investigate the catastrophe induced reconstruction labor price increases in the aftermath of natural disasters in the United States. To this end, we will not focus on insured losses of natural disasters only but rather try to describe the effect of Demand Surge on each potentially affected market participant. As the consequences of a catastrophe depend heavily on the characteristics of each affected region, we will further include additional regional economic variables in our analyses. Against this background, we analyze the impact of the catastrophe induced exogenous shock to the local labor market for reconstruction services. For this purpose, we answer the following two research questions:

- Under which economic conditions do catastrophes lead to a Demand Surge effect?
- What are the determinants for the magnitude of the Demand Surge effect?

Our results should be beneficial for various market participants. For example, governments have to deal with rising economic damages and a deep understanding of Demand Surge is necessary to apply appropriate price regulations; insurance companies are confronted with inflating claim levels and should consider Demand Surge with respect to premium calculation; building contractors could use this information for future capacity planning.

The empirical analyses are again based on catastrophe data provided by SHELDUS and pricing information in the construction sector available from Xactware. We analyze 9,009 natural catastrophe events in the United States between 2002 and 2010, and match these observations with pricing information in the construction sector. We find that the Demand Surge effect is more pronounced if regional wage differentials exist, i.e., a location which paid less than adjacent regions before a catastrophe will face a stronger wage increase because additional workers can only be attracted after the prevalent wage gap vanished. Moreover, wage increases are more pronounced if the local construction sector is in a growth stage and the GDP per worker in the construction sector is already high when a catastrophe occurs. In both situations, there is only little idle capacity in the construction sector and the imbalance between demand and supply is more distinct. The opposite effect can be observed if wages have already increased in the months prior to the catastrophe, which is due to saturation effects, and if regional unemployment rates are high so that the additional labor demand can be satisfied by unemployed. Finally, a higher number of insurance claims per event raises the wage surge, which indicates that the regulation policy of insurers is less restrictive if the total number of claims is large. The established empirical analyses are based on a paper written by Döhrmann et al. (2014).[101]

5.2 Literature Review

In addition to the literature review regarding Demand Surge models in theory and practice provided in Section 3.5, an overview of studies focusing on exogenous shocks on local labor markets and their corresponding wage effects in the short to medium term will be presented next.

Ex ante it is not clear how local labor markets react to exogenous shocks. Thus, a growing number of studies deal with exogenous demand and supply shocks and their potential consequences. The main focus of these studies is on the evolution of (un-)employment

[101] Throughout the remainder of this chapter we will assume that wages are proportional to labor costs, and, thus, our upcoming argumentation is only based on wages.

or the overall economic activity. For example, Guimaraes et al. (1993) analyze the economic consequences of Hurricane Hugo, which struck South Carolina in 1989 and was the economically most devastating storm in the history of the United States. They find that in the short run disasters may have a positive effect on the local economy and one of the sectors that benefited most was construction. In contrast, Ewing et al. (2009) conduct an impact assessment of the May 3, 1999, Oklahoma tornado on the Oklahoma City metropolitan statistical area. They observe an increase in employment growth and improved labor market stability measured in terms of volatility of the employment growth rate in the period following the tornado. In addition, Ewing and Kruse (2005) examine the impact of hurricanes during the 1990s on the unemployment rate in Wilmington (North Carolina), an area susceptible to hurricanes and tropical storms, and find an adverse impact in the short run but a positive impact in the long run. However, exogenous shocks to labor markets may not only be caused by natural disasters. Card (1990) analyzes the impact of the Mariel boatlift[102] on the Miami labor market. The massive labor force increase by 7% due to the mass immigration had no effect on wage rates. The studies most connected to our work are the ones of Belasen and Polachek (2008) and Belasen and Polachek (2009). Both studies investigate the effect of hurricanes in Florida on employment and earnings. Their studies are based on 19 hurricanes between 1988 and 2005 and the corresponding demand shock to the local labor market. They determine the change in average growth rate of employment and earnings of affected and neighboring counties relative to unaffected counties within the first quarter being hit by a hurricane. Their analysis is provided for the economy as a whole and five industrial sectors including construction. Nevertheless, these studies lack in providing an analysis of influencing factors of wage surge and an assessment of employment and earnings development in the quarters following the catastrophe.

Finally, Olsen and Porter (2010) and Olsen and Porter (2011b) provide an overview of studies trying to estimate the total damages of catastrophe events, which should include Demand Surge. In this context, approaches to consider wage increases are based on

[102] The Mariel boatlift was a mass immigration of Cubans towards the United States during the year 1980.

simulation studies,[103] or focus primarily on physical variables, such as the wind speed of a hurricane, to predict cost changes of constructed baskets of repairs.[104]

However, it is virtually unknown how local wages in the construction sector react to natural disasters in the short to medium term, in which economic situations catastrophes lead to Demand Surge effects, and which economic conditions influence the magnitude of the wage increase. This is the focus of this chapter.

5.3 Affected Market Participants

A deeper understanding of the Demand Surge effect is relevant for various market participants. In this section we briefly explain the influence of Demand Surge effects on affected market participants and their potential consequences.

In case of natural catastrophes, **governments** have to deal with high economic damages. In this context the consideration and the comprehension of Demand Surge is relevant for governments to ensure adequate catastrophe precautions and appropriate price regulations in the construction sector. Such official regulatory procedures allow governments to directly manage the Demand Surge. Price regulations are e.g. conceivable to restrict price increases after a catastrophe, but might also lead to a longer reconstruction period because fewer workers from other regions can be attracted. However, such regulations are only reasonable if the government understands the influence of Demand Surge on the social welfare. Indeed, it is not immediately clear if the Demand Surge effect has a negative influence on the social welfare because higher wages imply higher supply and, consequently, a faster remedying of damage and a decrease in underproduction.[105] In addition, the Demand Surge effect influences catastrophe induced public spending, for example for reconstruction of public infrastructure, like schools or highways. These damages can be quite substantial. For example, Guimaraes et al. (1993) declare that

[103] See Section 3.5.3.1.
[104] See Section 3.5.3.2.
[105] See Hallegatte et al. (2008) and Hallegatte (2008).

18,000 miles of highways in South Carolina were impaired by Hurricane Hugo in 1989. The impact of a resulting Demand Surge effect can be quantified with ζ as defined in equation 3.9, where p describes an index composed of necessary building services for reconstruction of public infrastructure.

While governments focus on economic damages, **insurance companies** have to deal with inflating claim levels due to rising reconstruction costs for insured and damaged properties. Against this background, it is worthwhile to note again that reconstruction labor is generally the key driver of increasing reconstruction costs as opposed to building materials (cf. Section 3.4). Thus, from an insurer's perspective, ζ quantifies the effect of Demand Surge regarding catastrophe-induced insurance payments, and p describes an index composed of necessary building services used for reconstruction purposes. Insurance companies should consider a Demand Surge effect when calculating insurance premiums and determining the required economic capital. Similarly, regarding regulatory capital backing standards, Demand Surge should be considered as well because in case of tail events, like natural disasters or terrorist attacks, the consideration of Demand Surge may decide whether the insurance company remains solvent or not.

For **investors** of insurance companies, estimates of catastrophe related claims payments and, thus, Demand Surge effects are relevant to assess the price reactions of insurance stocks after catastrophes. This effect regarding the market value of insurance companies $V^{(insurance)}$ is negative: $\frac{\partial V^{(insurance)}}{\partial \zeta} < 0$. However, investors have to consider that the market value does not only react with a decline due to claims payments, but there can be an opposing effect due to new premium income because of an increasing risk sensitivity of the population. As a consequence, the market value of insurance companies can even increase after catastrophes.[106]

Issuers and investors of **catastrophe-linked securities** have to quantify the price sensitivity of these securities owing to the occurrence of natural disasters including Demand Surge. Particularly for Cat Bonds with indemnity trigger, the payoff directly depends on the insured losses due to the catastrophe, so that Demand Surge is relevant for investors

[106] See Gangopadhyay et al. (2010), Lamb (1995), Marlett et al. (2000), and Shelor et al. (1992).

of these securities. As Demand Surge effects lead to a higher likelihood that the respective layer is affected, the market value of Cat Bonds $V^{(CAT)}$ is decreasing: $\frac{\partial V^{(CAT)}}{\partial \zeta} < 0$.

Last but not least, a Demand Surge effect is relevant for **building companies** since they have to estimate future demand which in turn depends on the price level to plan future capacities and profits in situations of catastrophe-induced reconstruction. Especially regarding recruitments, a detailed knowledge of the magnitude and duration of the Demand Surge effect is of crucial importance. In contrast to all other mentioned parties above, building companies can manage the quantity x(t) by increasing their capacity; only the total market-wide quantity of damages are exogenously given but the quantity x(t) of an individual building company is endogenous. Assuming that a building company is price taker, x(t) should be determined based on the following optimization problem: $argmax_{x(t),t=1,\ldots,T}\left\{V(P(1,T)|\Phi) = V\left(\sum_{t=1}^{T}\frac{p_{cat}(t)-c_{cat}(t)}{(1+r)^t}\cdot x(t)\right)\right\}$, where c_{cat} denominates the expenses in case of a catastrophe.

Thus, for all of these market participants, appropriately assessing Demand Surge should be useful.

5.4 Hypotheses

Next, we will present our hypotheses which will be tested in the empirical analyses in Section 5.6. In contrast to our analyses in Chapter 4 we will not only focus on insured losses but rather try to describe the impact of Demand Surge on each each potentially affected market participant as specified in Section 5.3. Nevertheless, some hypotheses are still identical to the ones formulated in Section 4.2. These are by name hypotheses H1, H5, and H6. Though, for the sake of completeness we will present these hypotheses again. In addition, we will include further regional economic variables and test their influence on Demand Surge to get a better understanding of the vulnerability of affected regions to the occurrence of Demand Surge effects. Since we investigated the influence of alternative catastrophes in close spatial and temporal proximity already in detail in Chapter 4 these variables will only be included as control variables in the upcoming analyses.

If the economy in the construction sector is growing, the demand for labor can arise fast but the labor supply reacts rather slowly, so that disposable capacities vanish. This leads to a lower potential to further increase the labor force and, as a consequence, a wage increase. Based on a simulation study Hallegatte et al. (2008) show that the Demand Surge effect for the 2004 and 2005 hurricane seasons would have been much lower if the economy had been in a recession as was the case for Hurricane Andrew in 1992. In a nutshell, we expect the

> *Growth Hypothesis (H1): In a stage of growth for the economy, Demand Surge levels are higher.*

An already high workload per employee in the construction sector prior to the catastrophe is associated with an overall good order situation. As a consequence, building contractors will only accept additional orders if the available labor capacity can be adapted to the change in demand. An adaption of labor force to the change in demand is possible by two ways. Either, workers are stimulated to work overtime which is associated with a premium, or building contractors can try to lure away workers from surrounding regions which is generally only possible if an attractive wage is offered to indemnify those workers for the cost of living away from home or temporally transfer their residence. Either way wages increase. Thus, we expect the

> *Workload Hypothesis (H2): A higher workload per employee in the construction sector increases the Demand Surge effect.*

If the unemployment rate in the catastrophe region is high, additional idle capacities are available. Therefore, unemployed can at least partially satisfy the additional labor demand in the construction sector due to the catastrophe. As a consequence, wage increases are less pronounced. Hence, we expect the

> *Unemployment Hypothesis (H3): Higher unemployment rates in the catastrophe region lessen the magnitude of Demand Surge.*

Obviously, it will be harder for catastrophe affected regions to attract additional labor force if the wage level in the catastrophe region is below adjacent regions. Generally, additional labor force from adjacent regions can be attracted only after the predominant wage gap vanished. This likely results in wage increases. In line with this argument, Morris (2005) supposes that the wage increases after Hurricane Katrina may be partly induced by wage differentials. Especially the regions hardest hit paid less and, therefore, wage increases were likely. Thus, we hypothesize the following

> *Wage Differential Hypothesis (H4): A predominant wage differential between the catastrophe affected and surrounding regions lead to higher Demand Surge levels.*

If the wage level is already high due to a construction boom or a reconstruction backlog from previous catastrophe events, this might lessen further wage increases due to saturation effects. First, workers from adjacent regions might commute to work in order to participate from an attractive wage level in the catastrophe region. If wages increase further, workers from regions more far away might be attracted that transfer at least temporally their residence. This second group is significantly larger than the first one. Thus, the potential work force is increasing above average with the preexisting wage level in the catastrophe affected region and, therefore, a new equilibrium state will be realized. Hallegatte et al. (2008) observe a similar effect regarding structural losses. Their simulated Demand Surge increases with rising structural losses but the slope decreases if losses increase further. Against this background, we expect the[107]

> *Saturation Hypothesis (H5): Higher wage levels in the construction sector lessen Demand Surge due to saturation effects.*

An increasing number of insurance claims per event can lead to a less thorough investigation of claims. This might be due to two possible reasons. On the one hand, there might be pressure of local authorities to settle claims quickly. As a consequence, insurance companies might either install untrained claim adjusters or each claim adjuster has to spend less time for each assessment. Both lead to a poorer damage assessment and, finally, inflating claim levels.[108] On the other hand, insurance companies might be classified by insured and media according to the way they settle claims, which might have a significant impact on their future premium income.[109] Thus, insurance companies might settle claims that are not directly attributable to the catastrophe itself due to fraud. To

[107] A similar but more detailed motivation of the saturation hypothesis can be found in Section 4.2.
[108] See Thomas (1976).
[109] See Olsen and Porter (2010).

provide some anecdotal evidence, Risk Management Solutions (2000) finds that insurance companies did not verify claims below a predefined level in the aftermath of the 1999 windstorms Lothar and Martin in France. Although a part of damaged properties might be repaired even without insurance, reconstruction is generally distributed over a longer time period and, therefore, the demand shock is less pronounced. In addition, Guimaraes et al. (1993) note that insurance payouts seem to motivate homeowners to expand and improve damaged properties, creating an additional labor demand. Against this backdrop, we hypothesize the following

> *Insurance Hypothesis (H6): A larger number of insurance claims per event lead to higher Demand Surge levels.*

5.5 Data and Empirical Strategy

Subsequently, we explain the measurement of Demand Surge and our empirical strategy. Lastly, we present relevant exogenous variables and descriptive statistics of our data set.

5.5.1 Catastrophe Events and Demand Surge

We measure Demand Surge on the basis of catastrophe events in the United States that are prone to Demand Surge. For this purpose, we use catastrophe data provided by SHELDUS.[110] As small catastrophe events are unlikely to produce the increasing labor demand that creates Demand Surge, we restrict our sample to observations with damage values above the 80% quantile of the empirical damage distribution (12.16 million US-$), i.e., we only include the 20% most destructive observations in our analysis.

The empirical implementation of our theoretical Demand Surge measures has already been described in Section 4.3.1. Nevertheless, we have to make reasonable assumptions regarding the unknown parameters of each measure again. These are in particular the

[110] For a detailed description of the SHELDUS database see Section 4.3.3.

point in time T of the last damage repair and the composition of the labor price index p(t). Furthermore, we have to identify a region (B) that satisfies the difference-in-differences assumption stated in equation 4.3.

As the date of the last damage repair is not known publicly, we test different reasonable values. For example, Belasen and Polachek (2008) and Belasen and Polachek (2009) state that even damages from the largest catastrophes in the past were repaired within two years. In line with this finding, Guimaraes et al. (1993) observe that often normal maintenance is combined with catastrophe related reconstruction in the first quarters following a catastrophe and, as a consequence, leads to a boost of reconstruction activity in the catastrophe region. This behavior can lead to a negative shock two years later. In addition, McCarty and Smith (2005) conducted an analysis of the 2004 hurricane season in Florida and found that one year later only 35% of damaged homes were repaired in full and in 16% of the cases reconstruction did not even start. Thus, a time period of one year and a corresponding value of $T = 1$ seems to be too short for our purposes. Nevertheless, Gron (1994) and Harrington (1997) declare that catastrophe claims are usually considered to be short tailed. Furthermore, Gron (1994) states that during the time period 1977 to 1986, 95% of homeowner's claims in the United States were paid within 3 years. In addition, with rising time horizons T a growing number of alternative catastrophes might occur within the calculation period of our Demand Surge measures. Thus, our results for longer time horizons are probably more heavily superimposed by wage increases resulting from alternative events. Against this background, we apply three different values of T, with $T = 2$ being our reference period, and $T = 1$ and $T = 3$ being lower and upper bounds in the upcoming empirical analyses.

Moreover, we require a wage index p(t) representing the bulk of building services needed for reconstruction after natural catastrophes on a regional scale to measure Demand Surge. Xactware offers such a retail labor index for 467 economic areas in the United States and Canada.[111] A detailed composition of the retail labor index has been provided in Table 4.1.

[111] For more information regarding Xactware and the provided retail labor index see Section 4.3.1.

Obviously, not every catastrophe region specified by SHELDUS is contained in Xactware. As we prefer to measure the Demand Surge effect in the center of each catastrophe region, we compute the closest Xactware localization available together with the distance between both localizations. To this end, we retrieve the geographic coordinates for each catastrophe region specified by SHELDUS and all available localizations in Xactware in WGS84. Next, we compute for each catastrophe region in SHELDUS the distances to all available Xactware localizations. Finally, we retrieve the retail labor time series for the Xactware localization with the shortest calculated distance.[112]

5.5.2 Empirical Strategy

The aim of the upcoming empirical analyses in Section 5.6 is twofold. First, we want to determine influencing factors of the occurrence of a substantial Demand Surge effect. Second, given such an observation we want to quantify the magnitude of the effect. In order to estimate the occurrence of substantial Demand Surge effects, we first have to provide a formal definition what we mean by substantial. Next, we will describe our approach to categorize each observation in our sample. To this end, we calculate for each localization specified by Xactware (county or MSA) and each point in time the average and maximum Demand Surge for different time periods of $T = 1$, 2, and 3 years irrespective of whether a catastrophe occurred in any combination of space and time. On the one hand, the subset of observations with high wage increases is of particular importance. On the other hand, it is reasonable to assume that observations with small wage increases are disproportionally affected by noise resulting from measuring problems. These might be a direct result of the fact that the nationwide wage evolution is not a perfect proxy for the unobservable wage evolution in the no-catastrophe scenario as opposed to the assumption in the implementation of the difference-in-differences approach. Against this background, we will only further investigate observations with high wage increases. The necessary threshold to classify an observation to have a substantial Demand Surge effect is based upon the empirical distribution of our Demand Surge variables. Thus,

[112] A more detailed description of the mapping algorithm is provided in Appendix 4.5.1.

in a second step, we calculate the mean μ and standard deviation σ for each empirical distribution of a Demand Surge measure. To this end, we include combinations of space and time that do not correspond to a catastrophe. In this case, a Demand Surge effect different from zero is due to measurement problems. We explicitly do not focus on non-catastrophic observations only because it is not clear which observations are completely non-catastrophic. As we assume that alternative catastrophes within a radius of 300 km in a time period from up to 3 years before to 3 years after the event affect the wage evolution of the county or MSA under observation, almost all observations are at least indirectly affected by a catastrophe. The respective statistical parameters can be found in Table 5.1.

Table 5.1: Distribution of Demand Surge.

The table shows mean and standard deviation of the average and maximum Demand Surge measures for different time horizons. The calculation is based on each possible combination of Xactware localization and point in time irrespective of whether a catastrophe occurred or not.

	Mean	Std. Dev.	Obs.
Average Demand Surge: 1 year (in %)	0.0427	2.1027	58,906
Average Demand Surge: 2 years (in %)	0.0964	3.2380	53,746
Average Demand Surge: 3 years (in %)	0.1596	4.2656	48,586
Maximum Demand Surge: 1 year (in %)	1.4833	2.8062	58,906
Maximum Demand Surge: 2 years (in %)	2.6142	4.4516	53,746
Maximum Demand Surge: 3 years (in %)	3.6980	5.9492	48,586

Finally, we define a Demand Surge effect of a given catastrophe region to be substantial if the respective Demand Surge effect is larger than $\mu + \sigma$:[113]

$$1_{\text{Demand Surge}} = \begin{cases} 1, & \text{if Demand Surge effect} \geq \mu + \sigma; \\ 0, & \text{otherwise.} \end{cases} \tag{5.1}$$

The first task is conducted with the help of a discrete choice model. To this end, we specify the probability of observing a substantial Demand Surge effect, given a set of covariates X, as our dependent variable: $P(1_{\text{Demand Surge}} = 1|X = x) = F(x'\beta)$. As a

[113]For all six Demand Surge measures the applied threshold $\mu + \sigma$ corresponds fairly close to the 90%-quantile of the respective Demand Surge distribution.

link function $F(\cdot)$ we use the logistic function $F(z) = e^z/(1+e^z)$, i.e., we subsequently conduct a logit analysis.[114] In this case, the estimation of the coefficient vector β is straightforward with maximum likelihood estimation. Based on the subset of observations with substantial Demand Surge effects, we additionally conduct a cross sectional regression analysis with robust standard errors to investigate the influence of the set of covariates X on the magnitude of the Demand Surge effect. Thus, we use a specification of the form: Demand Surge $= F(X, \beta) = X' \cdot \beta$.

5.5.3 Demand Surge Drivers

Direct damage values are reported by SHELDUS on a county level. Because different counties specified by SHELDUS as catastrophe regions regarding the same event may be mapped to the identical Xactware localization and all of our economic variables are related to this Xactware localization, we apply a reassessment algorithm that combines these observations into one single new observation. The new direct damage value is the sum of all combined original damage values. For our upcoming empirical analyses we define our direct damage variable as the sum of the damage in the catastrophe localization specified by Xactware and direct damages in a given radius of 300 km around this localization. Regarding the choice of the radius we also tested alternative radii of 150, 450, and 600 km. As a selection criterion we used the adjusted R^2 of models containing the direct damage variable and direct damages of previous and subsequent catastrophes within each potential radius together with year fixed effects. The corresponding results are presented in Tables 5.2 and 5.3.

[114] A detailed description of the logit analysis is provided in Appendix 5.8.1.

Table 5.2: Choice of Radius – OLS Model.

The table reports results of OLS regressions regarding the influence of damages in different radii on the average Demand Surge effect in a period of 2 years after the catastrophe. Model (A.1) considers damages within a radius of 150 km, model (A.2) refers to a radius of 300 km, model (A.3) to 450 km, and model (A.4) to 600 km. We report t-statistics in parentheses. The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	(A.1)	(A.2)	(A.3)	(A.4)
Damage	0.0791**	0.0437**	0.0777***	0.1123***
	(2.66)	(3.21)	(5.16)	(7.05)
Subsequent damage (0; 0.5]	0.0375**	0.0302**	0.0572***	0.0890***
	(2.64)	(3.09)	(5.88)	(6.89)
Subsequent damage (0.5; 1]	0.0160	0.0024	0.0028	-0.0435**
	(0.50)	(0.15)	(0.20)	(-2.91)
Subsequent damage (1; 1.5]	0.0981	1.2948***	0.7748**	0.0280
	(1.59)	(12.94)	(3.12)	(0.95)
Subsequent damage (1.5; 2]	-0.0526	-0.0234*	-0.4117**	-0.2020**
	(-0.90)	(-2.44)	(-3.25)	(-3.16)
Previous damage [0.5; 0)	0.1203**	0.0823***	0.1142***	0.1487***
	(2.82)	(3.98)	(5.27)	(8.11)
Previous damage [1; 0.5)	0.0738	-0.0024	-0.0085	-0.0160†
	(1.06)	(-0.23)	(-0.64)	(-1.80)
Previous damage [1.5; 1)	0.0411	-0.1131	-0.1311	-0.0449
	(0.49)	(-1.49)	(-1.23)	(-0.85)
Previous damage [2; 1.5)	-5.4524**	-1.3398***	-0.3078***	0.0163
	(-2.85)	(-4.26)	(-5.19)	(0.74)
Constant	5.7426***	5.4536***	5.4660***	5.6434***
	(34.90)	(29.14)	(22.00)	(22.06)
Year fixed effects	yes	yes	yes	yes
Observations	1,058	1,028	1,007	986
Adjusted R^2	0.232	0.550	0.496	0.371

Table 5.3: Choice of Radius – Logit Model.

The table reports results of logistic regressions regarding the influence of damages in different radii on the existence of a substantial Demand Surge effect measured as the average price increase in a period of 2 years after the catastrophe. Model (B.1) considers damages within a radius of 150 km, model (B.2) refers to a radius of 300 km, model (B.3) to 450 km, and model (B.4) to 600 km. We report z-values in parentheses. The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	(B.1)	(B.2)	(B.3)	(B.4)
Damage	0.3459***	0.0600***	0.0501***	0.0470***
	(3.93)	(4.09)	(7.25)	(9.84)
Subsequent damage (0; 0.5]	0.1658***	0.0369***	0.0376***	0.0404***
	(4.43)	(7.46)	(8.85)	(10.75)
Subsequent damage (0.5; 1]	0.0557*	0.0395***	0.0914**	0.0492***
	(2.38)	(4.24)	(2.80)	(9.43)
Subsequent damage (1; 1.5]	0.3820***	0.3074***	0.3150***	0.0896***
	(8.77)	(16.09)	(17.74)	(3.42)
Subsequent damage (1.5; 2]	0.0835*	0.0420***	-0.0981*	-0.0731*
	(2.42)	(6.68)	(-2.06)	(-2.01)
Previous damage [0.5; 0)	0.2890***	0.0526***	0.0413***	0.0425***
	(5.98)	(5.49)	(7.78)	(9.49)
Previous damage [1; 0.5)	0.1094	0.0360***	0.0037	-0.0122†
	(1.63)	(3.65)	(0.50)	(-1.96)
Previous damage [1.5; 1)	-0.0740	-0.0189*	-0.0193**	-0.0044
	(-1.49)	(-2.49)	(-3.11)	(-0.47)
Previous damage [2; 1.5)	-0.5702†	-0.0826	-0.0378	0.0067
	(-1.90)	(-1.10)	(-1.32)	(1.10)
Constant	-2.2754***	-2.4170***	-2.5293***	-2.7474***
	(-19.39)	(-19.25)	(-17.55)	(-16.59)
Year fixed effects	yes	yes	yes	yes
Observations	7,863	7,864	7,863	7,864
Adjusted McFadden R^2	0.165	0.160	0.178	0.161

To control for the effect of direct damages on Demand Surge, we included our damage variable and its corresponding quadratic. We also tested a linear specification and a version where we used a categorical damage variable with 10 different categories to describe the variation in our Demand Surge measure (cf. Table 5.4). Comparing these three models the combined linear and quadratic term model was the best with respect to the obtained adjusted R^2. As further control variables we only included year fixed effects and damage values for alternative catastrophes.

To control for the effect of alternative catastrophes with close temporal and spatial proximity, we calculate direct damages in a given radius of 300 km around each catastrophe region for different time intervals. We consider catastrophes up to 3 years before or after the end date of each catastrophe, depending on the chosen time horizon T. Because the availability of labor price data in Xactware starts in 2002, our sample of catastrophe events spans the time period of 2002-2010.

As an important influencing factor on Demand Surge we include the state of the economy in the construction sector and obtain a variable to test the growth hypothesis (H1). To this end, we use data from the Bureau of Economic Analysis, which provides yearly data regarding the real GDP in the construction sector on the MSA and state level. Obviously, the catastrophe affects the GDP at least in the year the catastrophe takes place. Thus, we compute the relative change in GDP between two and one year before the catastrophe, and use MSA data for localizations at the MSA level whereas using state data for counties in our sample.[115]

To test our workload hypothesis (H2) we calculate the real GDP per worker in the construction sector. Again, information regarding the real GDP in the construction sector stem from the BEA, whereas the number of workers in the construction sector is provided by the Bureau of Labor Statistics' QCEW program. All figures are either on the MSA or state level and refer to the realized ratio in the preceding year. The rationale behind this construction is that figures for the current year might be distorted by the catastrophe.

[115] All remaining observations at the county level are not part of any MSA in the United States.

Table 5.4: Functional Shape of Damage Variable.

The table reports results of OLS regressions regarding the influence of damage on the average Demand Surge effect in a period of 2 years after the catastrophe. We report t-statistics in parentheses. The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	(C.1)	(C.2)	(C.3)
Damage	0.0437**	1.0968***	
	(3.21)	(6.62)	
Damage^2		-0.0159***	
		(-6.84)	
Quantile 2 of damage			-0.7480
			(-1.37)
Quantile 3 of damage			0.7239
			(1.32)
Quantile 4 of damage			-0.2229
			(-0.41)
Quantile 5 of damage			0.6038
			(1.24)
Quantile 6 of damage			-0.0395
			(-0.08)
Quantile 7 of damage			-0.1193
			(-0.23)
Quantile 8 of damage			0.4518
			(1.07)
Quantile 9 of damage			-0.1997
			(-0.37)
Quantile 10 of damage			4.2485***
			(8.11)
Subsequent damage (0; 0.5]	0.0302**	0.0283**	0.0285**
	(3.09)	(2.80)	(2.60)
Subsequent damage (0.5; 1]	0.0024	-0.0193	-0.0079
	(0.15)	(-1.46)	(-0.50)
Subsequent damage (1; 1.5]	1.2948***	1.0938***	1.1709***
	(12.94)	(11.19)	(13.32)
Subsequent damage (1.5; 2]	-0.0234*	0.0033	0.0029
	(-2.44)	(0.36)	(0.31)
Previous damage [0.5; 0)	0.0823***	0.0751***	0.0540**
	(3.98)	(3.48)	(3.02)
Previous damage [1; 0.5)	-0.0024	0.0036	-0.0024
	(-0.23)	(0.44)	(-0.27)
Previous damage [1.5; 1)	-0.1131	-0.5635***	-0.2272**
	(-1.49)	(-5.48)	(-3.24)
Previous damage [2; 1.5)	-1.3398***	-0.7886**	-0.6025*
	(-4.26)	(-3.14)	(-2.33)
Constant	5.4536***	5.5157***	5.3802***
	(29.14)	(29.39)	(14.44)
Year fixed effects	yes	yes	yes
Observations	1,028	1,028	1,028
Adjusted R^2	0.550	0.604	0.602

To capture the effect of available idle capacities on Demand Surge, we additionally include the overall unemployment rate in the localizations specified by Xactware, and, hence, can inspect our unemployment hypothesis (H3). Thus, the unemployment rates are measured on the county or MSA level and refer to the realized value directly before the occurrence of the catastrophe. To this end, monthly unemployment data are provided by the Federal Reserve Economic Data (FRED) database maintained by the Federal Reserve Bank of St. Louis.

Wage differentials are measured using an approach comparable to the procedure described in Murphy and Hofler (1984). Based on the identified radius of 300 km we compute the average wage level of all Xactware localizations within a radius of 300 km. Then, we divide this average wage level by the wage level in the catastrophe region and, finally, subtract one. Thus, our measure for prevalent wage differentials describes the relative average increase in the wage level between the center of the catastrophe region and adjacent regions, measured in units of the catastrophe affected region, and, therefore, is suitable to verify the wage differential hypothesis (H4).

To measure saturation effects and subsequently test our saturation hypothesis (H5) we include the relative wage change in the foregoing 18 months. In so doing we are convinced to capture the effect of preceding wage increases on Demand Surge. As preceding wage increases might be triggered by alternative catastrophes in the past, we choose a time period long enough to cover the initial price jump of a potential hurricane event in the preceding hurricane season. Otherwise it would be possible that we only capture the already high wage level and see no further wage increase.

PCS provides information on the number of claims in different lines of business, including personal and commercial. All of these data are available on the state level and are assigned to each observation in our sample which is reported either on the MSA or county level. To test our insurance hypothesis (H6) we calculate the sum of the number of claims in commercial and personal lines of business.

Finally, we also include the distance in km between the catastrophe localization specified by SHELDUS and the assigned localization of economic variables as specified by Xactware. In the case that more than one catastrophe region of an event is mapped to the same Xactware localization, we use the mean value of the calculated distances. Based on the assumption that the Demand Surge effect in the center of the catastrophe region as specified by SHELDUS should be more pronounced compared to adjacent regions, the effect of the mapping distance on Demand Surge should be negative.

An overview together with a brief description of our set of explanatory variables is provided in Table 5.5.

Table 5.5: Variable Definitions.

Variable	Definition
Damage	Direct damage of the catastrophe region (in billion US-$).
Damage^2	Squared direct damage of the catastrophe region (in billion US-$).
Subsequent damage (a; b]	Direct damage of subsequent catastrophes in the same region that occurred in temporal proximity (in billion US-$); (a; b] denominates the time period in years with respect to the considered event.
Previous damage [a; b)	Direct damage of previous catastrophes in the same region that occurred in temporal proximity (in billion US-$); [a; b) denominates the time period in years with respect to the considered event.
GDP change	Real GDP growth of the construction sector in the affected MSA/state (in %).
GDP per worker	Real GDP per employee in the construction sector in the affected MSA/state (in thousands).
Unemployment rate	Unemployment rate in the affected county/MSA (in %).
Wage differential	Wage differential between the surrounding regions and the center of the catastrophe (in % of the wage level of the center).
Wage change	Relative change of wage in the construction sector during the 18 months before the catastrophe (in %).
Number of claims	Number of insurance claims (in thousands).
Mapping distance	Distance between the catastrophe (data from SHELDUS) and the assigned localization of economic variables (data from Xactware) (in km).

5.5.4 Descriptive Statistics

Descriptive statistics of our data set are provided in Tables 5.6 to 5.9. To provide an overview of the full sample which spans the time period 2002-2010, we report the distribution of catastrophes over years along with the type of catastrophe in Table 5.6. The number of observations is quite uniformly distributed across years except for the year 2008. While losses in this year were non extraordinary large, the number of events was the highest since 1998.[116] In addition, Panel B shows the types of disaster which are in 77% of the cases storms and in 21% floods. Against this background, we will split the sample in the upcoming empirical analyses into subsamples of storm and non-storm events.

Table 5.6: Summary Statistics – Composition of the Data Set.

	Observations	Percentage
Panel A: Year		
2002	810	8.99
2003	1,225	13.60
2004	970	10.77
2005	824	9.15
2006	957	10.62
2007	748	8.30
2008	1,438	15.96
2009	1,081	12.00
2010	956	10.61
Panel B: Type of Disaster		
Flood	1,879	20.86
Storm	6,973	77.40
Wildfire	80	0.89
Others	77	0.85

In Table 5.7 summary statistics are presented for each of our measures for Demand Surge. Panel A refers to the full sample of observations used in the upcoming logit analysis in Section 5.6.1. The mean Demand Surge effect varies between 0.4% and 0.8% and is highly right skewed. By definition, the maximum Demand Surge is larger than the

[116] See Insurance Information Institute (2009).

corresponding average Demand Surge. In Panel B the sample is restricted to observations with a substantial Demand Surge effect as defined in Section 5.5.2. This subsample is used in the following cross sectional regression analysis. Obviously the average Demand Surge is more pronounced in this case with values ranging from 6.0% to 10.4%. Again, the distribution is right skewed. Finally, the mean values for the maximum Demand Surge increase from Panel A to B and now vary from 9.2% to 18.0%.

Table 5.7: Summary Statistics – Demand Surge.

The table shows descriptive statistics of the average and maximum Demand Surge effect for different time periods after the catastrophes. In Panel A, data for the set of catastrophe events with damage values above the corresponding 80%-quantile of the empirical damage distribution is reported. Panel B focuses on the subset of catastrophe events with a substantial Demand Surge effect, i.e., a Demand Surge effect lying at least one standard deviation above the mean Demand Surge effect.

	Obs.	Mean	Std. Dev.	Min.	q25	q50	q75	Max.
Panel A: Demand Surge effect (in %)								
Avg. Dem. Surge: 1 year	9,009	0.4108	3.110	-6.914	-0.8896	-0.1708	0.8297	40.03
Avg. Dem. Surge: 2 years	8,053	0.5690	4.171	-9.557	-1.453	-0.1304	1.448	44.74
Avg. Dem. Surge: 3 years	6,972	0.8284	5.117	-11.47	-2.001	-0.0473	2.300	46.14
Max. Dem. Surge: 1 year	9,009	1.775	3.714	0	0	0.5363	2.009	50.05
Max. Dem. Surge: 2 years	8,053	3.146	5.221	0	0.0035	1.442	3.891	50.05
Max. Dem. Surge: 3 years	6,972	4.408	6.509	0	0.1991	2.290	5.684	63.34
Panel B: Substantial Demand Surge effect (in %)								
Avg. Dem. Surge: 1 year	1,075	6.029	5.940	2.159	2.853	3.882	6.016	40.03
Avg. Dem. Surge: 2 years	1,047	7.997	6.861	3.342	4.099	5.501	8.306	44.74
Avg. Dem. Surge: 3 years	891	10.36	7.486	4.453	5.907	7.707	11.43	46.14
Max. Dem. Surge: 1 year	1,033	9.156	7.084	4.300	5.164	6.676	9.553	50.05
Max. Dem. Surge: 2 years	1,018	13.63	8.184	7.076	8.565	10.17	15.57	50.05
Max. Dem. Surge: 3 years	877	17.97	8.932	9.657	11.39	15.07	20.74	63.34

Table 5.8 presents summary statistics for our set of explanatory variables. We included only observations with a damage value larger than the 80% quantile of the empirical damage distribution for the years 2002-2010. Thus, 9,009 out of originally 45,049 observations remain in the full sample. The distribution of our damage variable is right skewed with a mean value of 0.46 billion US-$, a median of 0.05 billion US-$, and a maximum of 71.51 billion US-$. Regarding subsequent and previous damages resulting from alternative catastrophes, we calculate direct damage values for time intervals of half a year up to 2 years before or after the considered event and choose a time interval of 1 year for

the remaining time horizon of 2 to 3 years before or after the event. The number of observations of subsequent damages in the time interval 2 to 3 years after a catastrophe differs from the rest as we excluded all observations in the year 2010 in this case. The reason is that our database of catastrophe events in the United States ends in 2012, and, therefore, we do not have the data available to calculate the subsequent damages for catastrophes occurring in 2010. Furthermore, nearly all observations sustain another catastrophe in a radius of 300 km during each of these time periods. Moreover, the variable GDP change is negative in more than 75% of the cases. This indicates that in most cases the economy has been in a recession and the construction sector possibly had idle capacities. A maximum wage change of 52.70% corresponds to the landfall of Hurricane Wilma in Melbourne (Florida) in October 2005. In this case, the current wage level is probably already highly driven by Demand Surge, as in the preceding 18 months Hurricanes Charley, Frances, and Jeanne occurred in Florida. The number of claims is only reported for storm events. This is due to the fact that damages owing to floods in the United States are insured by the NFIP and not by private insurance companies. As a result insured damages to properties resulting from floods are not covered by PCS. Regarding the mapping distance, which measures the distance between the catastrophe localization and the localization of the assigned economic variables, we discover a mean value of 45.91 km. Thus, in most of the cases we can find a good matching. The maximum value of 629 km refers to a catastrophe event in Alaska. If we would exclude all catastrophe events in Alaska, the maximum would substantially decrease to 267 km.

Finally, Table 5.9 presents pairwise correlations between the economic variables and the average Demand Surge for the 2 year time period.[117] Based on this univariate analysis, it can be noted that the correlation coefficients between almost all economic explanatory variables and the average Demand Surge have the expected sign based on the hypotheses in Section 5.4. The only exception in this regard is the positive correlation between wage change and the average Demand Surge that contradicts our saturation hypothesis (H5). Nevertheless, the coefficient is close to zero in this case and the wrong algebraic sign

[117] The pairwise correlations regarding the maximum Demand Surge for the 2 year time period are comparable to the average Demand Surge.

Table 5.8: Summary Statistics – Demand Surge Drivers.

The sample comprises 9,009 catastrophe regions with a damage value above the corresponding 80%-quantile of the empirical damage distribution. The table shows descriptive statistics of the set of independent variables, which is defined in Table 5.5.

	Obs.	Mean	Std. Dev.	Min.	q25	q50	q75	Max.
Damage (billion US-$)	9,009	0.4584	3.514	0.0122	0.0222	0.0525	0.1438	71.51
Subsq. damage (0; 0.5]	9,009	0.6170	4.679	0	0.0262	0.0737	0.2434	76.24
Subsq. damage (0.5; 1]	9,009	0.5792	4.537	0	0.0224	0.0715	0.2195	76.31
Subsq. damage (1; 1.5]	9,009	0.4301	1.324	0	0.0262	0.0783	0.2729	15.63
Subsq. damage (1.5; 2]	9,009	0.3761	2.437	0	0.0195	0.0591	0.1911	74.67
Subsq. damage (2; 3]	8,053	1.727	8.395	0	0.0976	0.2797	0.6842	76.39
Prev. damage [0.5; 0)	9,009	0.4837	3.469	0	0.0208	0.0637	0.1964	73.23
Prev. damage [1; 0.5)	9,009	0.3973	2.474	0	0.0234	0.0689	0.2363	73.21
Prev. damage [1.5; 1)	9,009	0.5908	4.212	0	0.0228	0.0741	0.2064	76.31
Prev. damage [2; 1.5)	9,009	0.2165	1.168	0	0.0210	0.0582	0.1736	72.09
Prev. damage [3; 2)	9,009	0.7768	2.989	0.0001	0.0868	0.1911	0.4724	72.92
GDP change (in %)	9,009	-4.372	6.902	-40.92	-8.108	-4.035	-0.6329	30.82
GDP per worker (thousands)	9,002	76.12	14.44	45.26	64.81	74.57	84.85	140.9
Unemployment rate (in %)	9,009	5.978	2.201	1.6	4.5	5.5	6.9	24.9
Wage differential (in %)	8,809	0.6984	6.516	-27.94	-3.939	0.6986	5.014	28.75
Wage change (in %)	8,992	7.795	5.933	-6.518	4.028	6.755	10.36	52.70
Number of claims (thousands)	6,973	1.813	11.55	0	0	0.0060	0.2820	372.6
Mapping distance (km)	9,009	45.91	29.45	0	27.99	42.35	59.60	629.0

might result from an omitted variable bias. Thus, in the next section we will analyze, whether or not these findings do still hold in a multivariate setting.

Table 5.9: Table of Correlations.

The table presents the pairwise correlations of catastrophe specific and macroeconomic variables.

	Avg. Dem. Surge	Damage	Damage^2	GDP change	GDP per worker	Unemp. rate	Wage differential	Wage change	No. of claims	Mapping distance
Avg. Demand Surge	1.00									
Damage	0.17	1.00								
Damage^2	0.07	0.96	1.00							
GDP change	0.16	0.06	0.03	1.00						
GDP per worker	0.10	0.02	-0.01	0.11	1.00					
Unemployment rate	-0.05	-0.02	-0.01	-0.09	-0.08	1.00				
Wage differential	0.13	-0.01	-0.00	0.00	-0.23	0.01	1.00			
Wage change	0.02	0.21	0.17	0.11	0.05	-0.11	-0.18	1.00		
Number of claims	0.19	0.40	0.36	0.05	0.05	-0.02	-0.03	0.10	1.00	
Mapping distance	-0.06	-0.02	-0.01	0.05	-0.14	-0.05	0.12	-0.04	-0.05	1.00

5.6 Empirical Results

5.6.1 Under which Conditions Do Catastrophes Lead to Demand Surge Effects?

Next, we will analyze which catastrophe specific and macroeconomic factors influence the occurrence of a substantial Demand Surge effect, i.e., we will test the hypotheses from Section 5.4. As already described in Section 5.5.2 a Demand Surge effect is defined to be substantial if its value lies at least one standard deviation above the mean Demand Surge of its empirical distribution. To exclude conceivably non catastrophic events, we only incorporated the 20% most devastating catastrophes in terms of direct damage during the time period 2002-2010.

Table 5.10 provides a group comparison of observations with substantial versus non-substantial Demand Surge. Results are provided for a group classification based on the average and maximum Demand Surge in a period of two years after the catastrophes. We report mean values for our set of explanatory variables for both groups together with the pairwise mean difference. Based on these results, we can confirm all of the hypotheses from Section 5.4 except the saturation hypothesis (H5). All pairwise differences have the expected sign and are highly statistically significant. An exception in this respect is only the variable Wage change, which measures wage increases in a period of 18 months prior to the catastrophe. In both settings the group of observations with substantial Demand Surge effects exhibit a higher preceding wage increase which contradicts our saturation hypothesis (H5).

Table 5.10: Group Comparison of Substantial and Non-Substantial Demand Surge.

The table reports the mean differences between the groups of substantial and non-substantial Demand Surge for several explanatory variables. In every setting the Demand Surge is calculated in a period of 2 years after the catastrophe. The other variables are defined in Table 5.5. We report t-statistics in parentheses. The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	Average Demand Surge			Maximum Demand Surge		
	Mean (subst.)	Mean (non-subst.)	Pairwise difference	Mean (subst.)	Mean (non-subst.)	Pairwise difference
Damage	2.057	0.2700	1.787***	1.724	0.3242	1.400***
			(14.41)			(11.13)
GDP change	-1.342	-3.5700	2.228***	-1.803	-3.496	1.693***
			(11.13)			(8.36)
GDP per worker	81.03	76.40	4.626***	82.16	76.25	5.916***
			(9.64)			(12.29)
Unemployment rate	5.202	5.697	-0.4949***	5.150	5.703	-0.553***
			(-7.91)			(-8.77)
Wage differential	2.495	0.4661	2.029***	2.278	0.5067	1.771***
			(9.41)			(8.09)
Wage change	9.122	8.591	0.5309**	8.940	8.620	0.321†
			(2.80)			(1.68)
Number of claims	6.538	1.239	5.299***	5.453	1.397	4.056***
			(11.51)			(8.74)
Mapping distance	44.06	46.12	-2.059*	43.38	46.22	-2.832**
			(-2.12)			(-2.89)

In addition, Table 5.11 provides results for the logit analysis based on the remaining 7,688 observations. Results for the average Demand Surge in a 2-year period after the catastrophe are provided in columns (A.1) to (A.3) and results for the corresponding maximum can be found in the following three columns (A.4) to (A.6). In addition, we investigate three different samples for each measure of Demand Surge: the full sample of observations (columns (A.1) and (A.4)), the subset of storm events (columns (A.2) and (A.5)), and the subsample of non-storm events only (columns (A.3) and (A.6)).

First, we will focus on the results for the average Demand Surge. Regarding the influence of damage we observe a statistically significant positive effect. This effect is particularly high for the subsample of non-storm events. If the damage increases by one standard deviation from $\mu - 0.5 \cdot \sigma$ to $\mu + 0.5 \cdot \sigma$, the probability of observing a substantial Demand Surge effect increases by 13.5 percentage points.[118]

[118] In the following, the impact of changing the explanatory variable by one standard deviation always

Table 5.11: Demand Surge for Different Samples – Logit Model.

The table reports results of logistic regressions regarding influencing factors of the occurrence of a substantial Demand Surge. Demand Surge is computed as the average/maximum increase of the retail labor index in a 2-year period after the catastrophe and the effect is assumed to be substantial if its value lies at least one standard deviation above the mean value of the empirical Demand Surge distribution. The other variables are defined in Table 5.5. We report z-values in parentheses and marginal effects at means in squared brackets ($-/+\ \sigma/2$). The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	Avg. Demand Surge (2 years)			Max. Demand Surge (2 years)		
	Full	Storm	Non-Storm	Full	Storm	Non-Storm
	(A.1)	(A.2)	(A.3)	(A.4)	(A.5)	(A.6)
Damage	0.0657***	0.0402***	0.3027***	0.0464***	0.0319***	0.0544**
	(4.81)	(3.62)	(3.96)	(6.02)	(3.42)	(3.16)
	[0.0202]	[0.0108]	[0.1345]	[0.0103]	[0.0065]	[0.0301]
GDP change	0.0253***	0.0313***	0.0118	0.0114†	0.0142†	0.0067
	(3.76)	(3.85)	(0.97)	(1.67)	(1.70)	(0.56)
	[0.0124]	[0.0139]	[0.0074]	[0.0040]	[0.0048]	[0.0050]
GDP per worker	0.0172***	0.0209***	0.0015	0.0157***	0.0172***	0.0073
	(5.42)	(5.62)	(0.25)	(4.77)	(4.43)	(1.11)
	[0.0200]	[0.0224]	[0.0022]	[0.0132]	[0.0140]	[0.0124]
Unemployment rate	-0.1053***	-0.0922**	-0.1347*	-0.1638***	-0.1457***	-0.2176***
	(-3.79)	(-2.85)	(-2.56)	(-5.48)	(-4.18)	(-3.86)
	[-0.0159]	[-0.0127]	[-0.0256]	[-0.0178]	[-0.0153]	[-0.0377]
Wage differential	0.0666***	0.0710***	0.0498***	0.0626***	0.0608***	0.0626***
	(10.26)	(9.18)	(3.92)	(9.17)	(7.47)	(4.68)
	[0.0347]	[0.0339]	[0.0326]	[0.0235]	[0.0220]	[0.0490]
Wage change	-0.0114	-0.0141	-0.0501*	-0.0097	-0.0169	-0.0111
	(-1.38)	(-1.44)	(-2.37)	(-1.08)	(-1.62)	(-0.50)
	[-0.0052]	[-0.0060]	[-0.0269]	[-0.0032]	[-0.0055]	[-0.0074]
Number of claims		0.0166***			0.0105**	
		(3.74)			(2.93)	
		[0.0149]			[0.0072]	
Mapping distance	-0.0001	0.0028†	-0.0081*	-0.0019	-0.0006	-0.0046
	(-0.07)	(1.66)	(-2.43)	(-1.19)	(-0.32)	(-1.36)
	[-0.0002]	[0.0056]	[-0.0215]	[-0.0029]	[-0.0009]	[-0.0146]
Constant	-3.1916***	-3.8585***	-0.4073	-2.4990***	-2.7276***	-1.2979
	(-8.53)	(-8.79)	(-0.55)	(-6.50)	(-6.19)	(-1.60)
Prev. and subsq. dam.	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	7,688	5,974	1,714	7,688	5,974	1,482
Adj. McFadden R^2	0.188	0.192	0.207	0.212	0.212	0.173

Both of our variables describing the state of the economy in the construction sector, GDP change and GDP per worker, are significant on the full sample and the subsample of storm events. Thus, both, a growing economy and a predominant higher workload in

refers to an increase of the considered variable from $\mu - 0.5 \cdot \sigma$ to $\mu + 0.5 \cdot \sigma$, and the other variables are at their means.

the construction sector have the hypothesized impact on the occurrence of a substantial Demand Surge effect. However, for non-storm events the coefficients have the expected sign but the results are not significant. Therefore, we can confirm our growth hypothesis (H1) and workload hypothesis (H2) for the full sample and the subsample of storm events.

In contrast, an increase of the unemployment rate by one standard deviation dampens the probability of substantial wage increases by 1 percentage point – 3 percentage points depending on the sample. Moreover, this effect is statistically significant which confirms our unemployment hypothesis (H3).

To test our wage differential hypothesis (H4) we include the variable Wage differential. We find that the coefficient is indeed positive and highly statistically significant. If wage differentials increase by one standard deviation the probability of a substantial Demand Surge effect rises by around 3 percentage points. To measure saturation effects we include the variable Wage change, which measures the relative wage increase in the preceding period of 18 months prior to the catastrophe. This effect is negative for all samples. Nonetheless, the effect is only significant for the subsample of non-storm events. Thus, we find only weak evidence for the saturation hypothesis (H5) based on the logit analysis.

As information regarding insured losses and the associated number of claims is only available for storm events, the variable number of claims is only contained in columns (A.2) and (A.5). Nonetheless, the number of claims has a significant positive effect on the probability of observing wage increases. Thus, the insurance hypothesis (H6) can be confirmed. It should be noticed that we observe this effect for a given damage, so that the coefficient of the number of claims does not reflect the indirect impact of a high damage. This result rather suggests a higher chance that insurance claims are settled if the total number of claims is high. This might be due to one of the two following reasons. On the one hand, the process of damage assessment might deteriorate due to pressure on insurance companies to settle claims quickly. On the other hand, the claims settlement behavior of insurers is observed in detail by insured and media in case of tail events, like natural catastrophes. A potential classification of insurers could have significant impact on future premium income, so that insurers might relax their claims settlement process, and, consequently, settle claims that are not attributable to the catastrophe itself.

When focusing on the analyses of the maximum Demand Surge, it can be noticed that for the subset of non-storm events the number of observations is lower compared to the number of observations for the average Demand Surge in column (A.3). This is due to the fact that none of the observations in 2009 have a substantial Demand Surge effect and this is fully captured by year fixed effects.

In summary, the results between the average and maximum Demand Surge vary only slightly in terms of absolute size and statistical significance. For example, the adjusted McFadden R^2 is quite similar with values ranging from 17.3% to 21.2% across all specifications. Furthermore, our results support the hypotheses H3, H4, and H6. Though, hypotheses H1 and H2 are confirmed for the full sample and the subsample of storm events, and hypothesis H5 can be confirmed for the set of non-storm events.

5.6.2 What are the Determinants for the Magnitude of the Demand Surge Effect?

Next, we analyze the influence of our set of explanatory variables on the magnitude of Demand Surge. For this purpose, we consider the subset of observations with a substantial Demand Surge effect. Thus, we exclude all observations with Demand Surge effects being less than $\mu + \sigma$. We analyze the impact of influencing factors using OLS regressions with robust standard errors. Again, in Table 5.12, columns (B.1) to (B.3) refer to the average Demand Surge in a time horizon of 2 years after the catastrophe, whereas columns (B.4) to (B.6) refer to the maximum Demand Surge. Moreover, we analyze three different samples: the full sample (columns (B.1) and (B.4)), the subset of storm observations (columns (B.2) and (B.5)), and the subset of non-storm observations only (columns (B.3) and (B.6)).

Table 5.12: Demand Surge for Different Samples – OLS Model.

The table reports results of OLS regressions regarding influencing factors of the average and maximum Demand Surge. The data set comprises catastrophe events with a Demand Surge of at least one standard deviation above the mean value of the empirical Demand Surge distribution. Demand Surge is computed as the average/maximum increase of the retail labor index in a 2-year period after the catastrophe. The other variables are defined in Table 5.5. We report t-statistics in parentheses. The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	Avg. Demand Surge (2 years)			Max. Demand Surge (2 years)		
	Full (B.1)	Storm (B.2)	Non-Storm (B.3)	Full (B.4)	Storm (B.5)	Non-Storm (B.6)
Damage	1.0537^{***}	1.0366^{***}	0.8337^{*}	1.3519^{***}	1.2739^{***}	1.2603^{**}
	(6.69)	(5.82)	(2.37)	(8.33)	(7.09)	(2.96)
Damage^2	-0.0149^{***}	-0.0151^{***}	-0.0115^{*}	-0.0191^{***}	-0.0183^{***}	-0.0177^{**}
	(-6.69)	(-6.07)	(-2.29)	(-8.09)	(-7.03)	(-2.85)
GDP change	0.1161^{**}	0.1346^{***}	0.0972	0.1484^{***}	0.1444^{***}	0.1746^{*}
	(3.28)	(3.53)	(1.21)	(4.88)	(4.57)	(2.09)
GDP per worker	0.0582^{***}	0.0514^{***}	0.0613^{**}	0.0648^{***}	0.0649^{***}	0.0532^{*}
	(5.69)	(4.26)	(2.87)	(5.80)	(4.94)	(2.30)
Unemployment rate	$-0.2061^{\dagger}$	-0.0983	-0.6307^{*}	-0.0830	-0.0152	-0.4178
	(-1.68)	(-0.73)	(-2.51)	(-0.59)	(-0.10)	(-1.30)
Wage differential	0.0712^{***}	0.0649^{**}	0.0960^{*}	0.1031^{***}	0.1070^{***}	0.1039^{*}
	(3.93)	(3.20)	(2.22)	(4.99)	(4.53)	(2.14)
Wage change	$-0.0598^{\dagger}$	-0.0630	-0.0098	-0.0278	-0.0402	0.0178
	(-1.69)	(-1.53)	(-0.14)	(-0.74)	(-0.90)	(0.22)
Number of claims		0.0102			0.0088	
		(1.21)			(0.95)	
Mapping distance	-0.0073	-0.0055	-0.0154	-0.0031	-0.0042	-0.0062
	(-1.57)	(-1.12)	(-1.29)	(-0.57)	(-0.68)	(-0.52)
Constant	2.9557^{*}	2.8897^{*}	$5.0112^{\dagger}$	5.4189^{***}	5.2655^{***}	7.6541^{**}
	(2.43)	(2.14)	(1.83)	(4.11)	(3.55)	(2.65)
Prev. and subsq. dam.	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	1,006	740	266	978	724	254
Adjusted R^2	0.621	0.672	0.444	0.676	0.710	0.547

First, we analyze the results of columns (B.1) to (B.3) which refer to the average Demand Surge in a time period of 2 years after the catastrophe. We find in each setting a concave relationship between our damage variable and the Demand Surge effect as the damage variable is positive and the damage squared is negative, with both coefficients being highly significant. Therefore, increasing damages lead to higher Demand Surge effects but the slope decreases as damages become even larger.

The effect of the state of the economy in the construction sector on Demand Surge is highly significant for the full sample and the subset of storm events. In addition, this effect is quite substantial. A one percentage point increase in the GDP of the construction sector in the preceding year leads to a 0.12 percentage point or 0.13 percentage point increase in Demand Surge. Thus, the Demand Surge effect is more pronounced if the economy is in a growth stage and the construction sector probably has less idle capacities. Hence, our growth hypothesis (H1) is confirmed.

In line with this finding, we find the effect of the workload in the construction sector indeed to be positive. A one standard deviation increase of the GDP per worker leads to a 0.7 to 0.9 percentage point increase in Demand Surge, and, therefore, acknowledges our workload hypothesis (H2).

To test our unemployment hypothesis (H3), we include the overall regional unemployment rate immediately before the occurrence of the catastrophe in our analyses. The negative effect on wage increases can be confirmed for the full sample and the subset of non-storm events. Hence, in these cases the additional labor demand can at least partially be satisfied by unemployed which dampens catastrophe induced wage increases.

In contrast, the effect of predominant wage differentials is significant for all samples. A ten percentage points more pronounced wage differential leads to a 0.65 to 0.96 percentage point increase in the average Demand Surge effect. This confirms our wage differential hypothesis (H4).

In Section 5.4 we argued that there could be saturation effects due to wage increases in the preceding period of 18 months. We find that this effect is only significant for the full sample with respect to the average Demand Surge, which is in line with our saturation hypothesis (H5). However, for all other settings the effect is not significant.

The effect of the number of insurance claims on Demand Surge is not statistically significant in all settings, so we cannot confirm the insurance hypothesis (H6).

If we analyze the maximum Demand Surge presented in columns (B.4) to (B.6), we find that most of the effects are quite similar with respect to the significance of the regression coefficients of our explanatory variables. Though, in most of the cases the absolute size of the coefficients is larger for the maximum Demand Surge. Nevertheless, there are some differences. The effect of preceding wage changes is not statistically significant in every setting for the maximum Demand Surge. In line with this finding, a higher unemployment rate has no significant restraining effect on Demand Surge too, irrespective of the considered sample. In contrast, the effect of predominant wage differentials is more pronounced. A ten percentage point increase in our wage differential measure leads to a 1.03 to 1.07 percentage points increase in Demand Surge.

In summary, no huge differences between the samples and Demand Surge measures (average versus maximum) can be observed. Moreover, the adjusted R^2 of up to 71% shows that most of the variation in our Demand Surge measures can be explained by the set of explanatory variables. Finally, our results support the hypotheses H1, H2, and H4, whereas hypothesis H3 and H5 can only be confirmed for the average Demand Surge. In contrast, our insurance hypothesis (H6) cannot be confirmed for both Demand Surge measures. This leads to the conclusion that the number of insurance claims can only help to explain the occurrence of a substantial Demand Surge effect but not its magnitude.

5.6.3 Robustness Checks

In Sections 5.6.1 and 5.6.2 we analyzed the effect of catastrophe specific and macroeconomic variables on the average and maximum Demand Surge in the following time period of 2 years. As already stated in Section 5.5.1, we believe that a time period of 2 years is reasonable, but as a robustness check we will also provide analyses for the average and maximum Demand Surge in time periods of 1 and 3 years after a catastrophe for the full sample of observations. For example, Gron (1994) finds that approximately 95% of homeowners' claims in the United States are paid within 3 years. Thus, at least all insured damages to properties should be repaired within a time horizon of 3 years. Against this background, we assume that a time horizon of 3 years is a good choice for an upper bound. In this case, one additional year is required to calculate our endogenous variable. As a consequence the number of observations is reduced to 6,810 instead of 7,688 for the 2-year period in the logit analysis. For the same reason, the sample increases to 8,788 when analyzing the 1-year Demand Surge. Table 5.13 provides an overview of the results regarding the average Demand Surge.

Table 5.13: Average Demand Surge for Alternative Specifications.

The table reports results of logistic and OLS regressions regarding influencing factors of the average Demand Surge in a period of 1 year after the catastrophe (models (C.1) and (C.3)) and a period of 3 years after the catastrophe (models (C.2) and (C.4)). The other variables are defined in Table 5.5. We report z-values/t-statistics in parentheses and marginal effects at means in squared brackets ($-/+\ \sigma/2$). The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	Logit		OLS	
	1 year (C.1)	3 years (C.2)	1 year (C.3)	3 years (C.4)
Damage	0.2046***	0.0519***	1.0802***	1.2451***
	(3.58)	(6.90)	(8.65)	(8.31)
	[0.0572]	[0.0162]		
Damage^2			-0.0149***	-0.0175***
			(-8.45)	(-7.98)
GDP change	0.0254***	0.0391***	0.0965**	0.1597***
	(4.25)	(5.27)	(2.79)	(4.26)
	[0.0135]	[0.0179]		
GDP per worker	0.0070*	0.0213***	0.0847***	0.0519***
	(2.21)	(5.73)	(7.57)	(4.71)
	[0.0078]	[0.0236]		
Unemployment rate	-0.0533*	-0.2001***	-0.1677	-0.0576
	(-2.24)	(-5.65)	(-1.48)	(-0.45)
	[-0.0090]	[-0.0218]		
Wage differential	0.0369***	0.0944***	0.0701***	0.0989***
	(5.87)	(12.99)	(3.57)	(5.22)
	[0.0187]	[0.0469]		
Wage change	-0.0075	-0.0138	-0.1691***	-0.0452
	(-0.96)	(-1.52)	(-6.21)	(-1.08)
	[-0.0034]	[-0.0063]		
Mapping distance	0.0002	-0.0009	-0.0236***	-0.0042
	(0.13)	(-0.56)	(-4.89)	(-0.78)
	[0.0004]	[-0.0019]		
Constant	-2.5473***	-3.3131***	1.0345	4.6698***
	(-7.10)	(-7.73)	(0.91)	(3.45)
Prev. and subsq. dam.	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	8,788	6,810	1,055	872
Adj. McFadden R^2 / Adj. R^2	0.195	0.236	0.475	0.671

First, according to columns (C.1) and (C.2), we observe that the effect of damage is decreasing with the time horizon T used to measure the Demand Surge, i.e., a one standard deviation increase in our damage variable leads to a positive change in the probability of observing a substantial Demand Surge effect, but with increasing values of T this effect decreases from 5.7 percentage points (T = 1) to 2.0 percentage points (T = 2) and finally 1.6 percentage points (T = 3). An opposite effect can be noticed regarding the influence of predominant wage differentials. In this case, the change in probability for a one standard deviation increase in wage differentials is more pronounced for longer time horizons. This time the probability of a substantial Demand Surge effect increases from 1.9 percentage points to 3.5 percentage points and finally reaches a value of 4.7 percentage points for the 3-year time horizon.

Regarding the analysis of the magnitude of the average Demand Surge most effects are similar to the results for the average Demand Surge for the full sample reported in Table 5.12. One minor difference is that the influence of a rising economy and prevalent wage differentials in the construction sector are highly significantly positive in all settings, but the economic effect is more pronounced for the 3-year time period. Furthermore, the effect of preceding wage increases on the average Demand Surge is not statistically significant in the 3-year time period. Finally, the adjusted R^2 is increasing with the time horizon used to measure the average Demand Surge. The lowest value can be observed for the 1 year setting (48%) and the highest for the 3 year setting (67%).

In line with the procedure for the average Demand Surge, we present the same analyses for the maximum Demand Surge in time periods of 1 and 3 years after the catastrophes in Table 5.14.

Regarding the results of the logit analyses, which are presented in columns (D.1) and (D.2), it can be stated that the findings for the maximum Demand Surge are similar to the ones for the average Demand Surge. Again, the effect of damage on Demand Surge is the highest for the 1-year time period. In contrast, the effect of prevalent wage differentials on the probability of observing a substantial Demand Surge effect is more pronounced for the 3-year time period.

Table 5.14: Maximum Demand Surge for Alternative Specifications.

The table reports results of logistic and OLS regressions regarding influencing factors of the maximum Demand Surge in a period of 1 year after the catastrophe (models (D.1) and (D.3)) and a period of 3 years after the catastrophe (models (D.2) and (D.4)). The other variables are defined in Table 5.5. We report z-values/t-statistics in parentheses and marginal effects at means in squared brackets ($-/+ \sigma/2$). The symbols †, *, **, *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively.

	Logit		OLS	
	1 year	3 years	1 year	3 years
	(D.1)	(D.2)	(D.3)	(D.4)
Damage	0.1242*	0.0469***	1.2805***	1.0591***
	(2.03)	(6.49)	(7.96)	(6.52)
	[0.0297]	[0.0119]		
Damage^2			-0.0178***	-0.0149***
			(-7.81)	(-6.21)
GDP change	0.0223***	0.0302***	0.1715***	0.2014***
	(3.39)	(3.69)	(4.11)	(5.53)
	[0.0102]	[0.0112]		
GDP per worker	0.0148***	0.0219***	0.0757***	0.0574***
	(4.54)	(5.62)	(5.59)	(4.96)
	[0.0143]	[0.0197]		
Unemployment rate	-0.0172	-0.1472***	-0.2117	-0.0476
	(-0.71)	(-4.25)	(-1.50)	(-0.40)
	[-0.0025]	[-0.0130]		
Wage differential	0.0563***	0.0853***	0.0734**	0.2042***
	(8.71)	(11.28)	(3.15)	(7.30)
	[0.0246]	[0.0344]		
Wage change	0.0011	-0.0097	-0.1659***	-0.0794
	(0.13)	(-1.02)	(-4.68)	(-1.44)
	[0.0004]	[-0.0036]		
Mapping distance	-0.0005	-0.0002	-0.0247***	-0.0010
	(-0.35)	(-0.11)	(-4.29)	(-0.15)
	[-0.0010]	[-0.0003]		
Constant	-3.4725***	-2.6845***	4.6496**	10.3543***
	(-9.53)	(-5.96)	(3.22)	(7.62)
Prev. and subsq. dam.	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	8,788	6,810	1,010	864
Adj. McFadden R^2 / Adj. R^2	0.203	0.281	0.453	0.666

Lastly, the adjusted McFadden R^2 increases from 20.3% ($T = 1$) to 21.2% ($T = 2$) and finally reaches a value of 28.1% ($T = 3$).

The results regarding the influence of catastrophe specific and macroeconomic factors on the magnitude of the maximum Demand Surge are provided in columns (D.3) and (D.4). In comparison with the full model for the 2-year time period in Table 5.12, most results are comparable. The relationship between damage and the maximum Demand Surge effect is concave for all considered time horizons. Furthermore, the effect of the unemployment rate is statistically not significant in all settings. In line with the findings for the average Demand Surge the positive effect of prevalent wage differentials is increasing with the time horizon T used for the calculation of the maximum Demand Surge. The effect of a percentage point increase in the measured wage differential increases from 0.07 percentage points (T = 1) to 0.10 percentage points (T = 2) and finally reaches a value of 0.20 percentage points (T = 3). The opposite effect can be observed regarding the prevailing workload in the construction sector. Last but not least, the effect of wage increases in the preceding period of 18 months prior to the catastrophe is only significantly negative for the 1-year time horizon.

5.7 Interim Results

In this chapter we have provided an analysis of increasing wages of skilled reconstruction labor in the aftermath of natural catastrophes in the United States. Our contribution is twofold. First, we identify catastrophe specific and macroeconomic conditions that lead to a substantial Demand Surge effect. Second, given this subset of observations with a substantial Demand Surge effect we quantify its magnitude and determinants. We believe that our results are beneficial for several market participants, including governments, insurance companies and their investors, building contractors, as well as issuers and investors of catastrophe linked securities, like, e.g., Cat Bonds. According to the results of our empirical analyses, almost all factors influencing the occurrence of a substantial Demand Surge effect are also able to quantify the magnitude. The results for the hypotheses analyzed in this chapter are summarized in Table 5.15. To be more specific, we identify a positive relationship between the GDP of the construction sector and Demand Surge. An increase of one percentage point in GDP prior to the catastrophe leads to a 0.12 percentage point increase in Demand Surge. In line with this finding, a higher workload in the construction sector pushes wages upward, too. A restraining effect can be observed for regions with higher unemployment rates. Thus, it seems that at least part of the additional labor demand can be satisfied by unemployed. In contrast, prevalent regional wage differentials have the opposite effect. In concrete terms, a ten percentage points more pronounced wage differential leads to a 0.7 percentage point increase in the average Demand Surge. Moreover, preceding wage increases in a time period of 18 months prior to the catastrophe event dampen further wage increases due to saturation effects. In contrast, a higher number of insurance claims per event only influences the probability of occurrence of a substantial Demand Surge effect but is not able to describe its magnitude. All of our results are confirmed by several robustness checks. Moreover, the adjusted R^2 with values up to 71% shows that our considered economic mechanisms are able to explain the variation in Demand Surge to a large extent. To sum up, our models are able to identify and quantify significant wage increases in the aftermath of natural disasters.

Table 5.15: Summary of Results.

The table summarizes the hypotheses and results regarding the positive or negative dependence of Demand Surge. Accordingly, the symbols ✓, (✓), and ○ denote the confirmation, partial confirmation, and non significance of each hypothesis.

Hypothesis	Variable	Expected sign	Results	
			Occurrence	Magnitude
H1: Growth hypothesis	GDP change	+	(✓)	✓
H2: Workload hypothesis	GDP per worker	+	✓	✓
H3: Unemployment hypothesis	Unemployment rate	−	✓	(✓)
H4: Wage differential hypothesis	Wage differential	+	✓	✓
H5: Saturation hypothesis	Wage change	−	(✓)	(✓)
H6: Insurance hypothesis	Number of claims	+	✓	○

5.8 Appendix

5.8.1 Logit Analysis

Similar to binary independent variables the outcome of a dependent variable can be binary too. In these cases the dependent variable can be coded as a dummy variable, where the 0/1 outcome is often a label for "no/yes". In our case the dependent variable $1_{\text{Demand Surge}}$ specifies whether a catastrophe region exhibits a substantial Demand Surge effect ($1_{\text{Demand Surge}} = 1$) or not ($1_{\text{Demand Surge}} = 0$). The aim is to specify the probability of observing a substantial Demand Surge effect given a set of covariates $X = (1, x_1, ..., x_k)$ in a way that:

$$\begin{aligned} &P(1_{\text{Demand Surge}} = 1|X) = F(X, \beta); \\ &P(1_{\text{Demand Surge}} = 0|X) = 1 - F(X, \beta). \end{aligned} \tag{5.2}$$

In this case β specifies the impact of X on the probability of observing a substantial Demand Surge effect. Since $E(1_{\text{Demand Surge}}|X) = 1 \cdot P(1_{\text{Demand Surge}} = 1|X) + 0 \cdot P(1_{\text{Demand Surge}} = 0|X)$ we can rewrite equation 5.2 as follows:

$$E(1_{\text{Demand Surge}}|X) = P(1_{\text{Demand Surge}} = 1|X) = F(X, \beta). \tag{5.3}$$

Against this background, the challenge is to specify a suitable function F. One possibility is to rely on the linear regression model: $F(X, \beta) = X' \cdot \beta$. The corresponding regression model is known as the linear probability model:

$$E(1_{\text{Demand Surge}}|x_1, ..., x_k) = P(1_{\text{Demand Surge}} = 1|x_1, ..., x_k) = \beta_0 + \beta_1 \cdot x_1 + ... + \beta_k \cdot x_k. \tag{5.4}$$

Thus, each coefficient β_j quantifies the influence of the independent variable x_j on the probability of observing a substantial Demand Surge effect. The main advantage of the linear probability model is the simple estimation technique needed to estimate the coefficient vector β. This task can be conducted with standard OLS. However, the disadvantages of this model specification are manifold. In theory, estimates for the dependent variable can be greater than one or less than zero, i.e., it is not possible to constrain $X' \cdot \beta$ to the $[0, 1]$ interval. A similar shortcoming can arise with respect to the estimated marginal effects. These can be greater than one or less than minus one. In addition the error term is not normally distributed and heteroskedastic. As a consequence the OLS estimator is not efficient and the corresponding standard errors are biased.[119] Therefore, the linear probability model is becoming less frequently used by econometricians.

Against this background, some of the above mentioned shortcomings could be removed if it would be possible to restrict the realization of the conditional expected value to the $[0, 1]$ interval. To this end, we apply a non-linear transformation of the following form:

$$\begin{aligned} E(1_{\text{Demand Surge}}|x_1, ..., x_k) &= P(1_{\text{Demand Surge}} = 1|x_1, ..., x_k) \\ &= F(X' \cdot \beta). \end{aligned} \tag{5.5}$$

In this context $F(\cdot)$ is a function with a co-domain limited to the $[0, 1]$ interval. In addition $F(\cdot)$ satisfies: $\lim_{z \to -\infty} F(z) = 0$ and $\lim_{z \to \infty} F(z) = 1$. In principle, any continuous cumulative distribution function over the real line will satisfy these conditions. One possible function $F(\cdot)$ satisfying the above stated constraints is the logistic function: $F(z) = \frac{e^z}{1+e^z} = \Lambda(z)$, where $\Lambda(\cdot)$ denotes the logistic cumulative distribution function. The corresponding regression model is known in literature as the logit model.[120] Another common link function used in econometric applications is the standard normal cumulative distribution function. The corresponding regression model is called probit model. In addition many other distributions have been suggested. For an overview see Greene (2001) and Aldrich and Nelson (1984). The question which model to choose is still unresolved, and the choice between a logit or probit model seems not to make much difference.

Finally, it is noteworthy to mention that the estimated coefficients of the model are not the marginal effects we are primarily interested in. In general, the marginal effect

[119] See Wooldridge (2013, p. 238 ff.) and Greene (2012, p. 727 ff.).
[120] See Wooldridge (2013, p. 560 ff.) and Greene (2012, p. 727 ff.).

of a continuous variable x_j on the probability of observing a substantial Demand Surge effect can be calculated as follows:

$$\frac{\partial E(1_{\text{Demand Surge}}|X)}{\partial x_j} = \left[\frac{dF(X' \cdot \beta)}{d(X' \cdot \beta)}\right] \cdot \beta_j = f(X' \cdot \beta) \cdot \beta_j, \tag{5.6}$$

where $f(\cdot)$ denotes the probability density function corresponding to the cumulative distribution function $F(\cdot)$. For the special case of a logit model the marginal effects can be calculated in the following manner:[121]

$$\frac{\partial E(1_{\text{Demand Surge}}|X)}{\partial x_j} = \left[\frac{d\Lambda(X' \cdot \beta)}{d(X' \cdot \beta)}\right] \cdot \beta_j = \Lambda(X' \cdot \beta) \cdot [1 - \Lambda(X' \cdot \beta)] \cdot \beta_j. \tag{5.7}$$

[121] See Greene (2012, p. 729 ff.).

6 Conclusion

At the beginning of this thesis, special attention has been drawn to the increasing economic and insured losses due to natural catastrophes in recent decades. The consequences of this development are manifold and affect several market participants. Thus, the need for a globally accepted risk management standard and vocabulary is even getting more and more important. Against this background, Chapter 2 has provided a risk management framework and explained several basic concepts of catastrophe risk management.

Chapter 3 has built the fundament for the following analyses. First, several definitions of the Demand Surge effect have been provided. Although Demand Surge is neither a new phenomenon nor limited to a particular region or type of catastrophe the literature still lacks a common definition and wording of this effect. Throughout this thesis, the term Demand Surge has been used to describe the sudden increase in prices for building materials and services needed for reconstruction after natural disasters. Second, we have found that building materials as opposed to building services nearly show any price reaction to the occurrence of a natural disaster. Thus, we have focused only on reconstruction labor wages in our empirical analyses and have found wage increases of at maximum 50% in the months following a catastrophe. A challenging task in this context has been the design of a measurement approach of Demand Surge effects. As the wage evolution is affected by the general economic trend and cyclical variations we have proposed a method that is able to segregate the catastrophe induced effect from the underlying evolution by using a difference-in-differences approach.

In Chapter 4 we have proposed an approach to quantify the Demand Surge effect from an insurer's point of view. The main objective has been to identify key drivers of the Demand Surge effect. The data set for the empirical analyses consists of pricing information in the construction sector provided by Xactware. These data are available since 2002 and have been matched with detailed information regarding natural catastrophes in the United States. To this end, we have been used two databases: EM-DAT and SHELDUS. To exclude conceivably non catastrophic events we have used a threshold of 100 million US-$ and 500 million US-$ for observations to be included in the sample. According to our econometric model, highly relevant drivers of Demand Surge are the amount of direct damage of a catastrophe together with direct damages of alternative events that occur in close proximity in terms of time in the same region. Furthermore, the model deduces a positive relationship between the number of settled insurance claims of an event and the Demand Surge effect. This has led to the conclusion, that the regulation policy of insurers is less restrictive if the total number of claims is large. Regarding the influence of the GDP in the construction sector we have identified a positive relationship, too. In a stage of growth in the economy idle capacities diminish, and, as a consequence, Demand Surge effects are higher. Moreover, we have discovered an ambiguous relationship between the number of establishments in the construction sector and the Demand Surge. Finally, we have observed saturation effects according to which a preceding wage increase dampens the Demand Surge effect. As saturation effects are more likely for extreme catastrophe events, it is not surprising that this observation holds only for the subsample of events with damages of at least 500 million US-$.

Based on the preceding findings, in Chapter 5 we have further investigated the Demand Surge effect. In contrast to the previous analyses the focus has been shifted towards an economic perspective instead of an insurer's point of view. Moreover, the conducted empirical analyses are only based on catastrophe data provided by SHELDUS. This is due to the fact that SHELDUS data are exclusively county-level data whereas catastrophe regions in EM-DAT are mainly specified on the state-level. This has enabled us to include several regional economic variables in our analyses. First, we have identified circumstances that promote the occurrence of a substantial Demand Surge effect. To this end, a logit analysis has been established. Second, given the subset of observations with substantial Demand Surge effects, we have further investigated influencing factors on Demand Surge. According to our results almost all factors influencing the occurrence of Demand Surge are also able to explain the magnitude of the effect. In addition to the identified influencing factors in Chapter 4 prevalent regional wage differentials have a positive effect on Demand Surge, too. If a catastrophe region paid historically less than adjacent regions the wage gap has to be vanished before new construction workers can be lured away from surrounding regions. As a consequence, the Demand Surge effect is more pronounced. Moreover, we have identified a positive relationship between Demand Surge and the workload in the construction sector. In contrast, we have found a restraining effect for regions with higher unemployment rates. Thus, it seems that at least part of the catastrophe induced additional labor demand can be satisfied by unemployed. Finally, the very high adjusted R^2 values of up to 71% show that a huge part of the variation in our Demand Surge measures can be attributed to the identified economic mechanisms.

We believe that our results are beneficial for several market participants. For example, governments are confronted with high economic damages in case of natural disasters. To apply adequate catastrophe precautions and appropriate price regulations a consideration and comprehension of Demand Surge is of crucial importance. In contrast, insurance companies have to deal with inflating claim levels due to rising reconstruction costs for damaged and insured properties. In this context, insurance companies should set insurance premiums properly including Demand Surge effects because in case of tail events, like natural disasters, considering Demand Surge can make the difference between solvency and insolvency. Regarding investors of insurance companies estimates of Demand Surge effects are relevant to assess price reactions of insurance stocks after catastrophes. On the other hand, issuers and investors of catastrophe-linked securities have to quantify the price sensitivity of these securities due to natural disasters including Demand Surge. Finally, building contractors have to estimate future demand which in turn depends on the price level to plan future capacities in situations of catastrophe induced reconstruction.

In this thesis, several aspects in the context of Demand Surge modeling have been highlighted and addressed. However, further research questions still remain unsolved. For example, we disregarded institutional, legal, political, and administrative constraints.[122] As an example, during the reconstruction period in Florida following the 2004 and 2005 hurricane seasons workers from outside the state were not allowed to enter Florida. As a consequence, Demand Surge effects were probably more pronounced, especially in the panhandle due to its remote location within Florida. Regarding the consequences of Hurricane Katrina in New Orleans additional issues have to be considered. Due to the massive destruction of the city the main issue was to reconstruct a whole city rather than just a few districts. Thus, reconstruction could start only after the city urban planning was finished. As a result, building permits were issued in delay and Demand Surge effects were probably limited.[123]

The remaining unexplained variability in our Demand Surge measures might be caused by several factors. For example, in our analysis we disregarded possible constraints comparable to the above mentioned institutional, legal, political, and administrative conditions associated with a catastrophe. Another influencing factor might be the media coverage. Media can attract interest and stimulate additional reconstruction activity which in turn influences the Demand Surge effect. Nevertheless, as our endogenous variable is not directly observable, and, therefore, our Demand Surge measures defined in Section 3.6 are only proxies for the actual Demand Surge effects, we might suffer explanatory power just due to an imprecise measurement of Demand Surge. In this context it is appropriate to raise the question whether the time series for the United States is a good choice for the baseline scenario in our measurement approach. As the counterfactual, i.e., the wage evolution in the no-catastrophe scenario, is not observable the task is to identify an alternative region that is similar to the catastrophe affected region in as many characteristics as possible. The natural choice would be to choose a region nearby as it is reasonable to assume that both regions are quite similar in many respects. Unfortunately, these regions are often affected by the treatment, which

[122] This restriction is comparable to Hallegatte et al. (2008).
[123] See Hallegatte (2008) and Hallegatte et al. (2008).

is a natural catastrophe in our case, too. Thus, to identify a proper control group is challenging and time-consuming. Anyway, at least the general economic trend and cyclical variations are reflected in the United States time series. Against this background, we believe that our choice of the United States time series as our baseline wage evolution is reasonable. However, some elaborate statistical methods like a propensity score matching might be valuable.[124]

In addition, it would be interesting to verify our empirical results for additional geographic regions, e.g., Central Europe or Australia. Up to date nearly all analyses apply to the United States. An exception in this respect is only the work conducted by McAneney (2007) which is related to Australia. As time passes by and more data become available it would be useful to investigate if the empirical results remain valid in the long run. All our current empirical analyses are restricted to the time period 2002 to 2010. According to the National Bureau of Economic Research (NBER) this time period covers only one business cycle.[125] Beyond that, the length of the Demand Surge effect might be another crucial issue. For example, building companies might decide to adapt their capacity to the change in demand. Thus, a detailed knowledge of the length is of vital importance for potential new hires. In this context, shortages of materials and equipment needed for reconstruction should be taken into account. In today's highly specialized economy little disruptions in the global supply chain can have huge impacts. If a lack of materials and equipment leads to longer reconstruction periods, indirect losses increase due to business interruptions. This in turn exacerbates reconstruction leading to a feedback loop. As a consequence, indirect losses increase nonlinear with rising direct losses as was already shown in Figure 2.1. In particular, the occurrence of indirect losses is not restricted to the catastrophe affected region but rather can occur worldwide due to the global interdependence of the world economy. A recent example would be the impact of the 2011 Tohoku earthquake in Japan on global IT supply chains. Last but not least, it

[124]For further information see Rosenbaum and Rubin (1983).
[125]See The National Bureau of Economic Research (2014).

would be interesting to analyze the predictive power of our empirical models. For many of the above mentioned market participants a reliable forecasting tool would generate significant benefit and would be a valuable source of information.

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