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Insured Loss Inflation: How Natural Catastrophes Affect Reconstruction Costs

by David Döhrmann^{*}, Marc Gürtler^{**}, and Martin Hibbeln^{***,§}

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Abstract

In the aftermath of a natural catastrophe, there is increased demand for skilled reconstruction labor, which leads to significant increases in reconstruction labor wages and hence insured losses. Such inflation effects are known as "Demand Surge" effects. It is important for insurance companies to properly account for these effects when calculating insurance premiums and determining economic capital. We propose an approach to quantifying the Demand Surge effect and present an econometric model for the effect that is based on 191 catastrophe events in the United States. Our model explains more than 75% of the variance of the Demand Surge effect and is thus able to identify the key drivers of the phenomenon.

JEL classification: G22, J23, J31, Q54, R23

Keywords: Demand Surge, Natural Catastrophes, Reconstruction, Insured Losses

1 Introduction

In recent decades, dramatic increases in the number and severity of catastrophes have been observed (Kunreuther/Michel-Kerjan, 2009). These developments are accompanied by a drastic increase in catastrophe-related economic losses, which is of particular relevance because growth in catastrophe losses is expected to continue for the foreseeable future, at least if effective disaster mitigation efforts are omitted (Pielke, 2005; Pielke et al., 2008).

The basis for economic losses is reconstruction costs, which must be raised after a catastrophe to restore the original state of buildings and infrastructure. To estimate future costs, however, it is not appropriate to apply the expected price level under normal conditions. Rather, it must be considered that, in the case of a catastrophe, there is increased demand for skilled labor and materials, which are necessary for reconstruction. Because this increase in demand is confronted with a constant supply of relevant goods and labor, significant price increases are expected, which in turn should be taken into account in the forecast of catastrophe losses. Such price effects are referred to as "Demand Surge" effects. According to the literature, "Demand Surge occurs 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 (and the insurer)" (EQECAT, 2005). Demand Surge is especially relevant for insurance companies because this effect may lead to significant additional losses in the context of the adjustment of claims. For example, it is estimated that the Demand Surge effect due to Hurricane Katrina is in the range of 30% to 40% (Munich Re, 2006).

Although Demand Surge is highly relevant for determining the economic damage of a catastrophe, there are only few contributions in the literature that address this phenomenon. This fact is even more surprising because it is a phenomenon that is neither new nor limited to a particular region or a particular type of catastrophe (Olsen/Porter, 2011a). Though, the scien-

tific 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 three main catastrophe modeling companies, Applied Insurance Research (AIR), EQECAT, and Risk Management Solutions (RMS), consider the Demand Surge effect within the framework of modeling direct catastrophe losses. However, the models of these companies are not publicly available. In particular, it is not clear which empirical results underlie their models.

Against this background, the present paper provides two main contributions. First, we propose an approach to quantify the Demand Surge effect. Second, we introduce the first econometric model for the effect. In this way, the paper provides a basis for the quantitative assessment of Demand Surge for future catastrophes, which, on one hand, is important for insurance companies when calculating insurance premiums and determining economic capital. 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.

Our empirical study is essentially based on data for natural catastrophes from the EM-DAT database and pricing information for the construction sector from Xactware. The dataset of EM-DAT has comprised worldwide information on natural catastrophes since 1900, and Xactware has been the leading provider of pricing information in the construction sector for more than 460 economic areas in the US and Canada since 2002. Our proposed Demand Surge model is able to explain more than 75% of the variance of the Demand Surge effect. Regarding possible influencing factors, we find that the Demand Surge effect strongly increases if the damage due to a catastrophe rises or if further catastrophes occur in close proximity in terms of time in the same region. In addition, we identify a strong positive relationship between the number of settled insurance claims for a catastrophe and Demand Surge, which indicates that the regulation policy of insurers is less restrictive if the total number of

claims is large. Furthermore, we show that the Demand Surge effect is particularly high if the construction sector is in a growth stage because in, such situations, there is little idle capacity. In contrast, we observe that a larger number of establishments in the construction sector leads to a decreasing Demand Surge effect because, in this situation, capacity adjustments can be conducted more easily. Finally, if we restrict the data to very severe catastrophes (i.e., damages of more than 500 million US-\$), we observe a saturation effect according to which the Demand Surge effect is reduced if wages for building services have already increased before a catastrophe.

The remainder of this paper is structured as follows. In Section 2, we provide a brief literature review regarding the Demand Surge effect and the derivation of hypotheses on the basis of common assertions from the literature. In Section 3, we develop a measure for Demand Surge and explain the relevant exogenous variables of the model. Furthermore, we present descriptive statistics of the data set. In Section 4, we discuss the empirical analyses and related robustness checks. In Section 5, we present our conclusions.

2 Modeling of Demand Surge and Hypotheses Development

2.1 Literature Review

Only two decades ago, researchers started to develop models to describe Demand Surge (Olsen/Porter, 2010). Leading among them are models developed by the three main catastrophe modeling companies, Applied Insurance Research, EQECAT, and Risk Management Solutions. All three steadily improve their models but withhold details as intellectual property. Nevertheless, a brief description of an early model developed by EQECAT can be found in Olsen/Porter (2011a).

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. It is noteworthy that they

focus only on wages, neglecting the price increases of building products. They propose a model based on the process of worker migration in response to price signals. However, the model results are not verified for other catastrophes. By contrast, Olsen/Porter (2011b) 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 fifty-two cities on the Atlantic and Gulf coasts. In their analysis, they focus primarily on physical variables, such as wind speed, and not on the economic mechanisms that underlie Demand Surge.

There are also a number of studies that consider a Demand Surge effect but mainly concentrate on estimating the total damages of catastrophe events (Florida International University, 2009; Hallegatte, 2008). The Florida Public Hurricane Loss Model (FPHLM) (Florida International University, 2009), which is restricted to hurricane events in Florida, 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. Hallegatte (2008) proposes an adaptive regional input-output (ARIO) model, which is used to simulate the economic consequences to the landfall of Katrina in Louisiana. 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. Based on simulations, a Demand Surge effect of 13% is calculated, but the most important result is nonlinearity between direct losses and total economic losses.

2.2 Impact on Labor and Material prices

According to the definition of Demand Surge, increases in both labor and material prices could be relevant and lead to higher costs. However, objective reasons and historical time

series data 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 the case of a catastrophe, labor demand increases sharply and exceeds the regional capacity. As a consequence, workers are stimulated to work overtime, which is associated with a premium. In addition, 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, making them 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. 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 (Hallegatte et al., 2008).

Example labor and material price evolutions can be found in Figures 1 and 2. Figure 1 shows labor price evolutions in West Palm Beach (Florida), Florida, and the US from 2003 to 2009, which include the landfall of Hurricane Frances in Q3 2004. Figure 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.

[Figure 1]

[Figure 2]

In summary, typically, 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/Porter (2011b) and AIR (2009). Olsen/Porter (2011b), for example, show that correlation between wind speed, as a proxy for damage, and material prices is low.

2.3 Hypotheses

In the literature, common themes of Demand Surge are discussed (Hallegatte et al., 2008; Olsen/Porter, 2011a) but have not yet been tested empirically. 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 (Hallegatte et al., 2008; Krutov, 2010; Olsen/Porter, 2011a). 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 (2009) 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 assessment. Alternatively, insurance companies might install untrained claim adjusters. Both lead to poorer damage assessments and, typically, increased payments (Thomas, 1976). 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 (Olsen/Porter, 2010). 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. As a consequence, insurance companies might settle claims that are not attributable to the catastrophe itself due to fraud. 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. Thus, we hypothesize:

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 price increases. In a simulation study, Hallegatte et al. (2008) show that the Demand Surge for the 2004 and 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:

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 (Olsen/Porter, 2011a). 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 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 Dollar, 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 one 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. As already mentioned in Section 2.2, 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:

Saturation Hypothesis (H6):

Higher wage levels in the construction sector lessen Demand Surge due to saturation effects.

3 Data

Subsequently, we first describe the construction of our measure for the Demand Surge effect. Then, we explain the measurement of relevant exogenous variables. Lastly, we present descriptive statistics of our data set.

3.1 Quantifying Demand Surge

3.1.1 Theoretical considerations and conversion into an empirical setting

In the remainder of this article, we calculate the Demand Surge effect from an insurer's point of view. In this case, an adequate calculation of Demand Surge can be represented as follows:

$$\text{Demand Surge} = \int_{t=0}^{t_{\text{end}}} p(t) \cdot \text{claims}(t) dt, \quad (1)$$

$$p(t) = p_{\text{cat}}(t) - p_{\text{no-cat}}(t), \quad (2)$$

where t_{end} denotes the date of the last settled claim related to the catastrophe under observation, $p(t)$ is the difference between the cumulative relative change of the observed labor price evolution and the cumulative relative change of a baseline labor price level at time t that would have been observed in a no-catastrophe scenario, and $\text{claims}(t)$ describes the timing of the claims settlement process with:

$$\int_{t=0}^{t_{\text{end}}} \text{claims}(t) dt = 1. \quad (3)$$

Unfortunately some of these data are not available. This is the case for $\text{claims}(t)$, t_{end} , and the baseline price level component $p_{\text{no-cat}}(t)$ in $p(t)$. Moreover, the composition of the labor price index $p(t)$ is not known in advance and depends on the type of catastrophe. To simplify

the calculation for the upcoming empirical analysis, we assume a uniform distribution for the claims settlement process:

$$\text{claims}(t) = \frac{1}{t_{\text{end}}}. \quad (4)$$

Regarding the choice of t_{end} , we will test different values because the date of the last settled claim is not known publicly. McCarty/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 $t_{\text{end}} = 1$ might be too short for our purposes. In addition, Belasen/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 (Harrington, 1997; Gron, 1994), and Gron (1994) argues that from 1977 to 1986, 95% of homeowners' claims in the United States were paid within 3 years. Against this background, we test three different values of t_{end} , with $t_{\text{end}} = 1$ being a lower bound, $t_{\text{end}} = 3$ being an upper bound, and $t_{\text{end}} = 2$ being our reference.

The price index $p(t)$ is modeled using the retail labor index of Xactware, a member of the Verisk Insurance Solutions Group. Xactware is the leading data provider for United States insurers, and the contained retail labor index is quite similar to building services chosen by AIR (2009) for reconstruction after storm losses. A detailed composition of the retail labor index is available in Table 1. We use the price evolution of building services in the United States for the baseline price level $p_{\text{no-cat}}(t)$. In the following Section, 3.1.2, a detailed description of our approach for measuring Demand Surge is given.

[Table 1]

3.1.2 *Measurement of Demand Surge*

We measure Demand Surge in the following manner. First, we identify relevant catastrophes in the United States that are prone to Demand Surge. Secondly, we track labor price

changes in the respective catastrophe areas. Lastly, we subtract a baseline price level to normalize the price evolution and obtain a Demand Surge measure.

For this purpose, we use catastrophe data provided by EM-DAT.¹ EM-DAT contains all natural and man-made catastrophes since 1900 that fulfill at least one of the following criteria: (1) 10 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 (Scheuren et al., 2008). The database is composed of data filed by UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies (Scheuren et al., 2008). All damage values therein are expressed in US dollars at the time the events took place (current value) and are converted into 2005 US dollars using the United States' Consumer Price Index (CPI) for comparison. Moreover, all these values refer to direct damage (Scheuren et al., 2008). Thus, indirect damages, i.e., the reduction of the total value added, are not contained (Hallegatte/Przyluski, 2010). Because small catastrophes are less likely to produce the increasing labor demand that creates Demand Surge effects, we use a cut-off value of 100 million US dollars for events in the sample.

The labor price increase in each catastrophe area is determined using a database compiled by Xactware. Xactware offers pricing information in the construction sector for more than 460 economic areas in the US 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 (Xactware, 2012). Obviously, the localizations in EM-DAT are usually not consistent with Xactware data. Because we are interested in the labor price increase in the center of each catastrophe region specified by EM-DAT, 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 sample and compute the closest Xactware localization available (the shortest distance between

¹ EM-DAT: The OFDA/CRED International Disaster Database – www.emdat.be – Université Catholique de Louvain – Brussels – Belgium.

two points on the surface of a sphere) for each of them. Then, we retrieve the corresponding retail labor index time series for this Xactware localization.

To measure the relative price increase due to a catastrophe, we calculate the cumulative relative change of the retail labor index for the catastrophe region starting at the time directly before the end of the catastrophe. As the price evolution of the retail labor index in the catastrophe region is affected by the general economic trend and cyclical variations, we have to normalize the retail labor index time series with a proxy for the unobservable price evolution for the hypothetical case that no catastrophe occurred (the counterfactual). We assume that both effects are contained in the US retail labor price index. Therefore, we additionally calculate the cumulative relative change for the US retail labor price index and calculate the difference of both cumulative relative changes, assuming that the gap between both time series is fully attributable to Demand Surge. Finally, we compute the mean value of the difference over differing time periods of 1, 2, or and 3 years and use the result as our Demand Surge measure. An example calculation is shown in Figure 3.

[Figure 3]

3.2 *Demand Surge Drivers*

For the direct damage caused by catastrophes, we rely on data from the EM-DAT database. These 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 in-

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. We observed that radii of up to 450 km had a significant effect on Demand Surge whereas damages within a distance of 450 km to 600 km were not significant. 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_{end} . 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. 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 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 Analyses (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. Quarterly data are available for each county, metropolitan statistical area (MSA) and state within the US.

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. 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 2.

[Table 2]

3.3 *Descriptive Statistics*

Summary statistics of our sample are presented in Tables 3 to 6. 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 3. 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 (Insurance Information Institute, 2009).

In Table 4a, 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 191 of 963 entries remain. The distribution of the damage is highly right skewed, with a mean value of 1.569 billion US-\$, a median of 0.2490 billion US-\$ 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. 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 49.11% 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 4b, the number of observations is further limited. The sample now comprises 59 catastrophe regions, with minimum sustained damages of 500 million US-\$. As a consequence, the mean value of the damage variable is significantly higher at 4.601 billion US-\$ compared to Table 4a. The same observation is true for the number of claims. All other exogenous variables are quite similarly distributed.

In Table 5, summary statistics are presented for each measure of Demand Surge, both for large (damage > 100 million US-\$) and extreme catastrophes (damage > 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 0.9% and 1.8%, whereas for extreme catastrophes, the Demand Surge effect is more pronounced, vary-

ing between 2.6% and 4.4%. The fact that the maxima remain the same both for large and extreme catastrophes points to the corollary that high Demand Surge effects correspond to high damages.

Finally, in Table 6 the pairwise correlations between the above-described variables are presented for the full sample of observations.

[Table 3]

[Table 4a]

[Table 4b]

[Table 5]

[Table 6]

4 Empirical Analyses

4.1 Demand Surge Effect for Large Catastrophes

Subsequently, we test our hypotheses from Section 2.3, which refer to the impact of catastrophe-specific variables and macroeconomic conditions on Demand Surge. According to Section 3, 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.² We analyze the resulting 179 observations using OLS regressions with clustered standard errors, each cluster representing one catastrophe. The results are presented in Table 7.

[Table 7]

In model (A.1), we test the influence of the damage caused by the catastrophe on Demand Surge. 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

² 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 3. However, due to the small sample size, this is not reasonable and, hence, has to be left for future research.

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% if damages due to a catastrophe rises 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. Rather astonishingly, alternative catastrophes that occur 12 to 18 months before the catastrophe seem to dampen the Demand Surge effect. An economic reasoning could be that preceding price increases are often triggered by previous catastrophe events, leading to saturation effects for price levels. A closer analysis in Section 4.2 confirms this assumption. 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 is generally in line with the finding that catastrophe insurance is short tailed; that is, homeowners' claims after catastrophes are usually paid quite promptly (Harrington, 1997).

In model (A.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 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 6). However, as both variables are considered in (A.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.

Moreover, we include the variable 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 not significant, showing that mapping seems to be appropriate.

When we integrate macroeconomic variables in model (A.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. Not only is the effect 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%. 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.

In Section 2.3 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 negative, but the effect is not statistically significant.

In summary, most effects are very stable in terms of statistical significance and absolute size. Our results suggest that hypotheses H1-H5 are true. On the contrary, a cost increase of building services in the period before a catastrophe does not lead to a significant reduction in Demand Surge, so we cannot confirm hypothesis H6. However, it may be possible that saturation is only relevant for even more severe catastrophe events. Furthermore, the adjusted R^2 of up to 0.764 shows that Demand Surge can, to a large extent, be attributed to the considered effects.

4.2 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 178 to 55. The consequence is a low number of degrees of freedom, which can easily lead to the problem of overfitting the data. 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. However, we make an exception for the variables Wage change and Previous Damage [1.5; 1). 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 a catastrophe, Wage change captures the effect of price increases for building services in the foregoing 18 months. However, both variables may measure the same economic effect because preceding price increases are often triggered by previous catastrophe events. 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.1), 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 0.43. Against this background, we only include the variable Wage change in model (B.2) to measure potential saturation effects. Moreover, because a saturation effect is most likely for catastrophes with very high damages, it is reasonable that this effect is more pronounced if we restrict the data to even more severe catastrophes.

[Table 8]

The regression results for the subsample of extreme events are presented in Table 8. The first column is a repetition of model (A.4) to allow easier comparison of the results. Model (B.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 0.766, instead of 0.764. In model (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. 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 significant, with $p < 5\%$. Concretely, a cost increase of building services in the preceding 18 months of 10% dampens the Demand Surge effect by 1.6%. Thus, for extreme catastrophes, saturation effects cause that Demand Surge to indeed be less pronounced, which confirms the *saturation hypothesis (H6)*.

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 0.860 suggests that, even if the set of explanatory variables is significantly reduced, Demand Surge can largely be explained by the considered economic effects.

4.3 Robustness Checks

4.3.1 Average Demand Surge effect within differing time periods

In Sections 4.1 and 4.2, we analyzed the effect of several influencing factors on the average Demand Surge after large 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 (Harrington, 1997). 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 9. 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 155 if we consider all events with damages of at least 100 million US-\$ (instead of 179 observations for the 2-year period). Models (C.1), (C.2) and (C.3) contain the results for catastrophes with damages of at least 100 million US-\$; model (C.4) refer 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 4.1 and 4.2, in terms of both statistical significance and the magnitude of the effects. According to the procedure in Section 4.2, we restrict our set of explanatory variables in model (C.3) to variables where we found significant effects on the full model (C.2). Moreover, for the reason mentioned in the description of Table 8, we include the variable Wage change instead of Previous Damage [1.5; 1) in model (C.3). The adjusted R^2 values of these models are even slightly higher compared to the analysis in Sections 4.1 and 4.2, with values of 0.797 instead of 0.764

for the larger sample and 0.890 instead of 0.860 if the data set is constrained to extreme catastrophes.

[Table 9]

Similarly, we present the results regarding a one-year period for the average Demand Surge effect in Table 10. Because the required observation period is shorter, we have 191 available observations instead of 179. 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/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 10]

4.3.2 *Maximum instead of average Demand Surge effect*

As described in Section 3.1.1, 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. Even if the concrete distribution is not observable, it is 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 11. We find that the results are not substantially different from the analyses of the average Demand Surge effect in Sections 4.1 and 4.2, 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 even higher than in 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 as well as a preceding wage increase for building services lead to a less pronounced Demand Surge, whereas a larger number of claims per event increase the Demand Surge effect. Thus, hypotheses H1-H3, H5, and H6 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 (model (E.2) and (E.3)). 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 hypothesis H4 cannot be confirmed only because the data set is not sufficiently large. Hence, this hypothesis should be re-tested if more data are available to achieve greater clarity.

[Table 11]

5 Conclusions and Implications

In this paper, we propose an approach to quantifying the Demand Surge effect and provide the first econometric analysis of the effect. Our econometric model is able to explain more than 75% 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 1.8%. 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 0.25%. 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 strictly decreasing relationship between the number of establishments in the construction sector and the Demand Surge because a larger number of establishments implies a greater ability to adjust the capacity in the construction sector. In addition, if we restrict the data to damages of at least 500 million US-\$, we observe a saturation effect, according to which a wage increase for building services before a catastrophe leads to a reduced Demand Surge effect. It must be emphasized that this effect is not statistically significant if we consider smaller catastrophes because a saturation effect is most likely for catastrophes with very high damages.

Our results 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 (see Gangopadhyay et al., 2010; Lamb, 1995; Marlett et al., 2000; Shelor et al., 1992). 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 catastrophes. Thus, for all of these market participants, our results should be useful for appropriately assessing Demand Surge effects.

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TABLES & FIGURES

Table 1: Composition of the retail labor index

Composition	
Carpenter – Finish, Trim/Cabinet	Heating/A.C. Mechanic
Carpenter – General Framers	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	

Table 2: Variable definitions

Variable	Definition
Damage	Direct damage of the catastrophe (in US-\$ billion).
Subsequent damage (a; b]	Direct damage of subsequent catastrophes that occurred in geographical and temporal proximity (in US-\$ billion); (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 US-\$ billion); [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/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).

TABLES & FIGURES

Table 3: Summary statistics - composition of the data set

	Obs.	Percentage
<i>Panel A: Year</i>		
2002	13	6.81
2003	22	11.52
2004	19	9.95
2005	16	8.38
2006	18	9.42
2007	22	11.52
2008	45	23.56
2009	24	12.57
2010	12	6.28
<i>Panel B: Type of disaster</i>		
Flood	23	12.04
Storm	159	83.25
Local Storm	95	49.74
Tropical Cyclone	49	25.65
Extratropical Cyclone (Winter Storm)	2	1.05
Not further specified	13	6.81
Wildfire	9	4.71

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Table 4a: Summary statistics – Demand Surge drivers (damage > US-\$ 100 million)

The sample comprises 191 catastrophe regions with a minimum damage of US-\$ 100 million. The table shows descriptive statistics of our set of independent variables, which is defined in Table 2.

	Obs.	Mean	Std. Dev.	Min.	q25	q50	q75	Max.
Damage (US-\$ billions)	191	1.569	5.153	0.1020	0.1529	0.2490	0.6083	41.01
Subsequent damage (0; 0.5]	191	1.614	8.471	0	0	0.0634	0.3508	110.99
Subsequent damage (0.5; 1]	191	0.9820	4.998	0	0	0.0392	0.2210	57.34
Subsequent damage (1; 1.5]	191	0.8361	2.708	0	0	0.0594	0.4143	21.90
Subsequent damage (1.5; 2]	191	0.3562	1.156	0	0	0.0667	0.2135	10.29
Subsequent damage (2; 3]	191	1.856	6.488	0	0	0.1792	0.5821	62.48
Previous damage [0.5; 0)	191	1.080	4.986	0	0	0.0439	0.2361	57.34
Previous damage [1; 0.5)	191	0.8459	3.967	0	0	0.0795	0.2358	32.57
Previous damage [1.5; 1)	191	0.3518	2.238	0	0	0.0574	0.1805	30.23
Previous damage [2; 1.5)	191	0.3787	2.482	0	0	0.0074	0.1028	32.57
Previous damage [3; 2)	191	1.162	4.979	0	0.0396	0.1764	0.4661	62.48
Claims (millions)	191	0.2730	0.3668	0.0028	0.0560	0.1300	0.2894	1.385
GDP change	191	-0.0385	0.0452	-0.2074	-0.0634	-0.0343	-0.0084	0.0630
Establishments ('000)	191	18.82	15.84	0.0500	8.163	12.55	26.71	79.90
Wage change	190	0.0864	0.0625	0.0036	0.0518	0.0735	0.0997	0.4911
Mapping distance (km)	191	4.520	14.35	0	0	0	0	84.19

TABLES & FIGURES

Table 4b: Summary statistics – Demand Surge drivers (damage > US-\$ 500 million)

The sample comprises 59 catastrophe regions with a minimum damage of US-\$ 500 million. The table shows descriptive statistics of our set of independent variables, which is defined in Table 2.

	Obs.	Mean	Std. Dev.	Min.	q25	q50	q75	Max.
Damage (US-\$ billions)	59	4.601	8.569	0.5035	0.6777	1.587	4.558	41.01
Subsequent damage (0; 0.5]	59	2.039	4.358	0	0	0.0685	1.751	21.90
Subsequent damage (0.5; 1]	59	1.534	4.847	0	0	0.0439	0.5227	32.57
Subsequent damage (1; 1.5]	59	1.685	4.595	0	0	0.0021	0.2069	21.90
Subsequent damage (1.5; 2]	59	0.1131	0.2512	0	0	0	0.1220	1.574
Subsequent damage (2; 3]	59	0.8244	2.871	0	0.0748	0.1582	0.4979	21.42
Previous damage [0.5; 0)	59	1.985	4.728	0	0	0.1421	1.096	16.28
Previous damage [1; 0.5)	59	1.487	5.638	0	0	0.1171	0.3538	30.23
Previous damage [1.5; 1)	59	0.7112	3.929	0	0.0018	0.1033	0.1719	30.23
Previous damage [2; 1.5)	59	0.1712	0.7074	0	0	0.0071	0.0692	5.140
Previous damage [3; 2)	59	0.7724	1.558	0	0	0.1713	0.4661	5.617
Claims (millions)	59	0.4786	0.4806	0.0180	0.0870	0.2710	0.6042	1.385
GDP change	59	-0.0290	0.0548	-0.2074	-0.0634	-0.0287	-0.0057	0.0630
Establishments ('000)	59	20.25	17.73	0.0500	8.552	11.82	26.88	67.13
Wage change	59	0.1047	0.0925	0.0036	0.0578	0.0760	0.1048	0.4911
Mapping distance (km)	59	6.059	15.19	0	0	0	0	80.35

TABLES & FIGURES

Table 5: 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.
<i>Panel A: Large catastrophes (damage > \$100 million)</i>								
Avg. Demand Surge: 1 year	191	0.0094	0.0330	-0.0419	-0.0072	0.0011	0.0100	0.2190
Avg. Demand Surge: 2 years	179	0.0133	0.0477	-0.0666	-0.0116	0.0012	0.0175	0.3119
Avg. Demand Surge: 3 years	155	0.0180	0.0589	-0.0776	-0.0124	0.0064	0.0280	0.3466
Max. Demand Surge: 2 years	179	0.0326	0.0660	-0.0119	-0.0003	0.0125	0.0403	0.4449
<i>Panel B: Extreme catastrophes (damage > \$500 million)</i>								
Avg. Demand Surge: 1 year	59	0.0260	0.0509	-0.0171	-0.0047	0.0030	0.0365	0.2190
Avg. Demand Surge: 2 years	55	0.0354	0.0733	-0.0236	-0.0058	0.0102	0.0383	0.3119
Avg. Demand Surge: 3 years	48	0.0440	0.0893	-0.0335	-0.0079	0.0152	0.0407	0.3466
Max. Demand Surge: 2 years	55	0.0613	0.1033	-0.0068	0.0002	0.0263	0.0615	0.4449

TABLES & FIGURES

Table 6: 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	0.44	1.00					
Claims	0.32	0.47	1.00				
GDP change	0.42	0.16	0.17	1.00			
Establishments	0.02	-0.07	-0.03	0.01	1.00		
Wage change	0.07	0.33	0.27	0.36	0.01	1.00	
Mapping distance	0.14	0.17	0.12	0.17	-0.32	0.05	1.00

Table 7: 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 2. 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	0.0022*** (4.84)	0.0017*** (4.47)	0.0016*** (4.87)	0.0018*** (4.94)
Subsequent Damage (0; 0.5]	0.0012*** (6.95)	0.0012*** (7.22)	0.0012*** (7.87)	0.0012*** (7.36)
Subsequent Damage (0.5; 1]	0.0017*** (3.93)	0.0016*** (3.68)	0.0014*** (3.82)	0.0013*** (3.63)
Subsequent Damage (1; 1.5]	0.0090*** (5.28)	0.0092*** (5.49)	0.0087*** (5.30)	0.0084*** (5.28)
Subsequent Damage (1.5; 2]	-0.0002 (-0.22)	0.0003 (0.43)	0.0010 [†] (1.97)	0.0007 (1.38)
Previous Damage [0.5; 0)	0.0022** (3.23)	0.0021** (3.35)	0.0020** (3.40)	0.0020*** (3.60)
Previous Damage [1; 0.5)	-0.0002 (-0.73)	-0.0003 (-1.34)	-0.0007* (-2.01)	-0.0003 (-0.82)
Previous Damage [1.5; 1)	-0.0009** (-3.22)	-0.0010*** (-3.90)	-0.0020*** (-4.62)	-0.0014* (-2.31)
Previous Damage [2; 1.5)	-0.0006 (-1.16)	-0.0005 (-0.94)	-0.0007 (-1.45)	-0.0007 (-1.47)
Claims		0.0146* (2.65)	0.0132* (2.18)	0.0136* (2.41)
GDP change			0.2496** (3.34)	0.2564** (3.28)
Establishments			-0.0003 [†] (-1.79)	-0.0003 [†] (-1.79)
Wage change				-0.0482 (-0.98)
Mapping distance		0.0001 (1.49)	-0.0000 (-0.51)	-0.0001 (-0.58)
Constant	-0.0036 (-1.36)	-0.0076** (-2.77)	0.0085 [†] (1.83)	0.0125 [†] (1.84)
Observations	179	179	179	178
Adjusted R^2	0.717	0.726	0.764	0.764

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Table 8: 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 2. 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)
Damage	0.0018*** (4.94)	0.0019*** (4.96)	0.0012*** (3.84)
Subsequent Damage (0; 0.5]	0.0012*** (7.36)	0.0013*** (7.92)	0.0049*** (3.81)
Subsequent Damage (0.5; 1]	0.0013*** (3.63)	0.0013*** (3.58)	0.0017* (2.48)
Subsequent Damage (1; 1.5]	0.0084*** (5.28)	0.0082*** (5.18)	0.0063*** (4.47)
Subsequent Damage (1.5; 2]	0.0007 (1.38)		
Previous Damage [0.5; 0)	0.0020*** (3.60)	0.0021*** (4.07)	0.0039*** (3.91)
Previous Damage [1; 0.5)	-0.0003 (-0.82)		
Previous Damage [1.5; 1)	-0.0014* (-2.31)		
Previous Damage [2; 1.5)	-0.0007 (-1.47)		
Claims	0.0136* (2.41)	0.0136* (2.53)	0.0213** (3.25)
GDP change	0.2564** (3.28)	0.2409** (3.33)	0.1905 (1.62)
Establishments	-0.0003† (-1.79)	-0.0003† (-1.90)	-0.0007** (-3.02)
Wage change	-0.0482 (-0.98)	-0.0888* (-2.30)	-0.1555* (-2.56)
Mapping distance	-0.0001 (-0.58)		
Constant	0.0125† (1.84)	0.0140* (2.43)	0.0212* (2.11)
Observations	178	178	55
Adjusted R^2	0.764	0.766	0.860

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Table 9: 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. Model (C.1), (C.2) and (C.3) refer to catastrophes with total damage of at least 100 million US-\$, whereas the relevant barrier for model (C.4) is 500 million US-\$. The other variables are defined in Table 2. We report t-statistics in parentheses. The symbols +, *, **, *** indicate statistical significance at the 10 %, 5 %, 1 %, and 0.1 % level, respectively.

	Damage \geq 100 mio. \$			Damage \geq 500 mio. \$
	(C.1)	(C.2)	(C.3)	(C.4)
Damage	0.0023*** (6.09)	0.0019*** (7.07)	0.0021*** (7.07)	0.0015*** (4.70)
Subsequent Damage (0; 0.5]	0.0015*** (8.83)	0.0015*** (10.60)	0.0015*** (12.20)	0.0049** (2.96)
Subsequent Damage (0.5; 1]	0.0021*** (4.45)	0.0017*** (4.49)	0.0017*** (4.55)	0.0019* (2.47)
Subsequent Damage (1; 1.5]	0.0109*** (5.16)	0.0095*** (4.89)	0.0093*** (4.86)	0.0073*** (4.39)
Subsequent Damage (1.5; 2]	-0.0006 (-0.39)	0.0014 (1.44)		
Subsequent Damage (2; 3]	0.0006*** (5.78)	0.0004* (2.11)	0.0005* (2.53)	0.0009† (2.03)
Previous Damage [0.5; 0)	0.0025* (2.53)	0.0024** (2.82)	0.0024** (3.29)	0.0048** (3.53)
Previous Damage [1; 0.5)	-0.0002 (-0.84)	-0.0007 (-1.44)		
Previous Damage [1.5; 1)	-0.0012** (-3.40)	-0.0021** (-2.85)		
Previous Damage [2; 1.5)	-0.0006 (-0.96)	-0.0008 (-1.55)		
Previous Damage [3; 2)	-0.0001 (-0.25)	-0.0002† (-1.71)		
Claims		0.0106† (1.92)	0.0104* (2.05)	0.0153† (2.02)
GDP change		0.4251*** (5.25)	0.3867*** (4.95)	0.3011* (2.50)
Establishments		-0.0003 (-1.47)	-0.0002 (-1.49)	-0.0006* (-2.24)
Wage change		-0.0652 (-1.06)	-0.1293** (-2.83)	-0.1937* (-2.80)
Mapping distance		-0.0001 (-0.74)		
Constant	-0.0049 (-1.52)	0.0202* (2.13)	0.0217** (2.87)	0.0282* (2.41)
Observations	155	155	155	48
Adjusted R^2	0.739	0.797	0.798	0.890

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Table 10: 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. Model (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 2. We report t-statistics in parentheses. The symbols +, *, **, *** indicate statistical significance at the 10 %, 5 %, 1 %, and 0.1 % level, respectively.

	Damage \geq 100 mio. \$			Damage \geq 500 mio. \$
	(D.1)	(D.2)	(D.3)	(D.4)
Damage	0.0024* (2.38)	0.0024** (2.73)	0.0023** (2.78)	0.0012* (2.53)
Subsequent Damage (0; 0.5]	0.0009* (2.28)	0.0010*** (3.47)	0.0010*** (3.50)	0.0051*** (4.32)
Subsequent Damage (0.5; 1]	0.0016* (2.28)	0.0010* (2.12)	0.0010* (2.11)	0.0005 (0.99)
Previous Damage [0.5; 0)	0.0025* (2.04)	0.0025** (2.76)	0.0024** (2.79)	0.0042*** (4.80)
Previous Damage [1; 0.5)	-0.0004 (-1.54)	0.0001 (0.28)		
Claims		0.0122** (3.28)	0.0122** (3.26)	0.0195** (3.53)
GDP change		0.2353*** (3.52)	0.2363*** (3.59)	0.2247** (2.85)
Establishments		0.0001 (0.50)	0.0001 (0.57)	-0.0004† (-1.91)
Wage change		-0.1727** (-3.23)	-0.1696*** (-3.67)	-0.2307*** (-4.79)
Mapping distance		0.0000 (0.07)		
Constant	0.0003 (0.15)	0.0197** (2.71)	0.0195** (3.04)	0.0306** (3.44)
Observations	191	190	190	59
Adjusted R^2	0.459	0.582	0.586	0.764

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Table 11: 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. Model (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 2. We report t-statistics in parentheses. The symbols +, *, **, *** indicate statistical significance at the 10 %, 5 %, 1 %, and 0.1 % level, respectively.

	Damage \geq 100 mio. \$			Damage \geq 500 mio. \$
	(E.1)	(E.2)	(E.3)	(E.4)
Damage	0.0027*** (5.27)	0.0022*** (4.71)	0.0023*** (4.92)	0.0012* (2.74)
Subsequent Damage (0; 0.5]	0.0021*** (11.15)	0.0021*** (11.32)	0.0022*** (12.38)	0.0069** (3.67)
Subsequent Damage (0.5; 1]	0.0028*** (4.79)	0.0024*** (4.66)	0.0024*** (4.64)	0.0027* (2.64)
Subsequent Damage (1; 1.5]	0.0130*** (4.70)	0.0122*** (4.63)	0.0120*** (4.62)	0.0101*** (5.36)
Subsequent Damage (1.5; 2]	0.0001 (0.14)	0.0010 (1.02)		
Previous Damage [0.5; 0)	0.0027* (2.43)	0.0026** (2.70)	0.0026** (2.87)	0.0056** (3.56)
Previous Damage [1; 0.5)	-0.0005* (-2.30)	-0.0004 (-0.63)		
Previous Damage [1.5; 1)	-0.0008* (-2.21)	-0.0010 (-1.08)		
Previous Damage [2; 1.5)	-0.0007 (-1.03)	-0.0008 (-1.25)		
Claims		0.0159** (2.97)	0.0160** (3.04)	0.0244** (2.78)
GDP change		0.2829** (3.10)	0.2733** (3.14)	0.1852 (1.20)
Establishments		-0.0003 (-1.54)	-0.0003† (-1.76)	-0.0012** (-3.53)
Wage change		-0.0932 (-1.25)	-0.1272* (-2.61)	-0.1737* (-2.05)
Mapping distance		0.0000 (0.33)		
Constant	0.0085** (2.75)	0.0291** (3.16)	0.0313*** (4.01)	0.0423** (3.01)
Observations	179	178	178	55
Adjusted R^2	0.767	0.800	0.804	0.877

Figure 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.

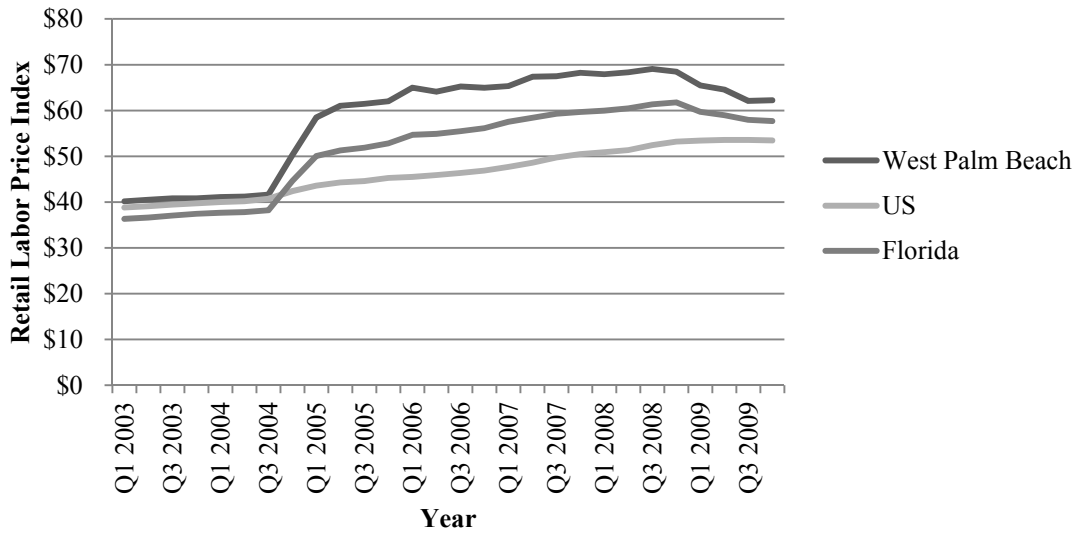


Figure 2: Building Material Price Index

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

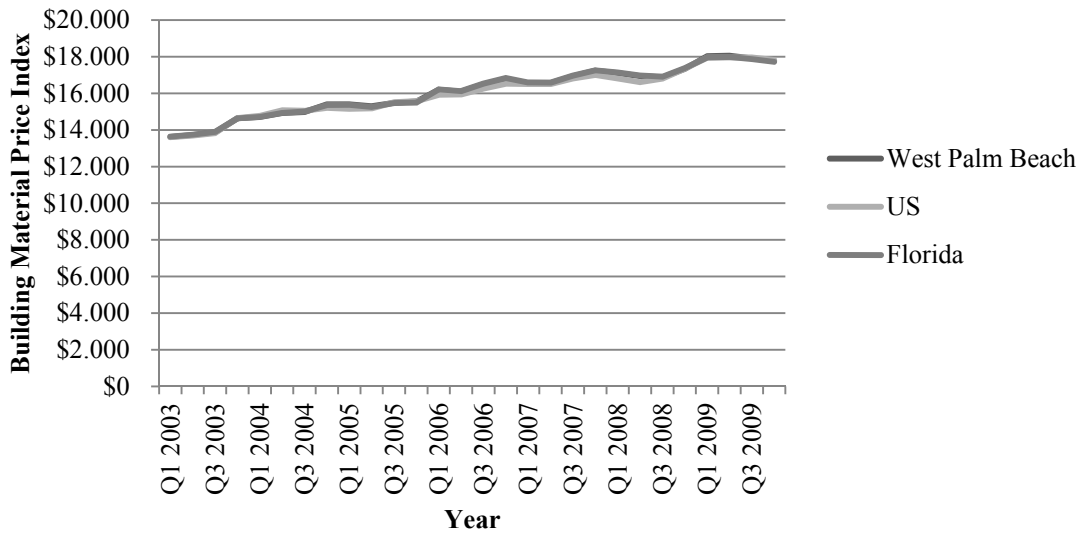


Figure 3: Demand Surge Measurement

In this figure our measurement of Demand Surge is depicted. We compute the cumulative relative change of the retail labor price index in West Palm Beach (p_{cat}) and the entire US (p_{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 cumulative relative changes defined as $p(t)$. Finally, we calculate the mean value of $p(t)$ over differing time periods of 1, 2 or 3 years.

