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An Econometric Analysis of the Demand Surge Effect

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Abstract

In case of a natural catastrophe there is an increased demand for skilled labor and materials which in turn leads to significant price increases that should be taken into account in the forecast of catastrophe losses. Such price effects are referred to as "Demand Surge" effects. The paper at hand presents an extensive econometric analysis and modeling of the Demand Surge effect. We find that Demand Surge is positively influenced by the total amount of repair work, by alternative catastrophes in the same region in close temporal proximity, and by a higher amount of insurance claims per event. Furthermore, the Demand Surge effect is more pronounced if the construction sector is in a growth stage. In contrast, a higher capacity of the construction sector has a restraining effect on Demand Surge. In addition, if we restrict the data to very severe catastrophes, we observe a saturation effect according to which a wage increase for building services before a catastrophe reduces the Demand Surge effect.

Keywords: Demand Surge, natural disasters, empirical analysis, insurance

JEL classification: D45, J2, J31, Q54, R15, R23, R32

1 Introduction

In recent decades, a dramatic increase in the number and severity of catastrophes has been observed (Kunreuther/Michel-Kerjan, 2009). These developments are accompanied by a drastic increase in catastrophe-related economic losses. This is of particular relevance because the 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).

Basis of economic losses are reconstruction costs that must be raised after a catastrophe to restore the original state of buildings and infrastructure. In order 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 case of a catastrophe there is an increased demand for skilled labor and materials, which are necessary for the 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). A consideration of Demand Surge is especially for insurance companies of high relevance because this effect may lead to significant additional losses in the context of the adjustment of claims. E.g., for hurricane Katrina the Demand Surge was assumed to lie in the range of 30 % to 40 % (Munich Re, 2006).

Although Demand Surge is of high relevance for the economic damage of a catastrophe, there are only few contributions in the scientific literature that deal with this phenomenon. This is all the more surprising, as it is a globally relevant phenomenon that is neither new nor limited to a particular region or a particular type of catastrophe (Olsen/Porter, 2011a). But the scientific literature considers Demand Surge exclusively on a qualitative level or only for a specific catastrophe type or event, so that universally valid quantitative models for Demand Surge have not previously 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. Particularly, it is not clear which empirical results underlie their models.

Against this background, the main motivation and the contribution of the present paper lies in an extensive econometric analysis and modeling of Demand Surge. By this means, the pa-

per provides the basis for a quantitative assessment of Demand Surge for future catastrophes. On the one hand, this is important for insurance companies and governments to ensure appropriate catastrophe precautions. On the other hand, such information is relevant for issuers and investors of catastrophe-linked securities (such as Cat Bonds), who have to consider Demand Surge within the framework of security pricing, as well as for building companies, whose future capacities and profits in situations of reconstruction highly depend on Demand Surge.

Our empirical study is essentially based on data about natural catastrophes from the EM-DAT database and on pricing information about the construction sector of Xactware. The dataset of EM-DAT comprises worldwide information on natural catastrophes since 1900 and Xactware is 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 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 proximity of time in the same region. In addition, we identify a strong positive relationship between the number of regulated insurance claims of a catastrophe and Demand Surge, which indicates that regulation policy of the insurers is less restrictive if the total number of claims is high. Furthermore, we show that the Demand Surge effect is particularly high if the construction sector is in a growth stage because in such a situation there is only little idle capacity. In contrast, we observe that a higher number of establishments of 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. Section 2 contains a brief literature review regarding the Demand Surge effect and the derivation of hypotheses on the basis of common assertions of 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. The empirical analyses and related robustness checks are content of Section 4. Our conclusions are presented in Section 5.

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 the increasing reconstruction costs in the aftermath of the 2004 and 2005 hurricane season in Florida. It is noteworthy that they focus only on wages, whereas price increases of building products are neglected. They propose a model based on a process of worker migration in response to price signals. However, the model results are not verified for another catastrophe. Olsen/Porter (2011) instead 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 of nine hurricane seasons and fifty-two cities on the Atlantic and Gulf coast. However in their analysis they focus mainly on physical variables like wind speed and not on economic mechanisms that underlie Demand Surge.

Furthermore, there exist some studies that consider a Demand Surge effect, but mainly concentrate on estimating the total damage 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, region of Florida and the estimated statewide loss before applying the Demand Surge function. Hallegatte (2008) instead proposes an adaptive regional input-output (ARIO) model, which is used to simulate the economic consequences in Louisiana to the landfall of Katrina. Its innovations are 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, both increases in 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 are in 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 the regional capacity. As a consequence, workers are stimulated to work overtime which is associated with a premium. In addition, import of labor is associated with extra costs for accommodation and traveling. On the contrary, building materials are traded on global markets and can be transported to devastated areas more easily, therefore being less volatile. Nonetheless exceptions are possible. For example, the regional cement price rose significantly after the landfall of Katrina due to the fact that cement was imported mainly through the harbor of New Orleans, which had a bounded capacity during that time (Hallegatte et al., 2008).

Exemplary labor and material price evolutions can be found in Figures 1 and 2. Figure 1 shows the labor price evolution in West Palm Beach, Florida and the US from 2003 to 2009 including the landfall of hurricane Frances in Q3 2004. On the contrary, Figure 2 plots the respective material price evolution. While the sharp increase in labor prices coincides with the landfall of Frances, the material prices react rarely, pointing again to the fact that labor prices are in the center of attention.

[Figure 1]

[Figure 2]

Summing up, typically the labor capacity seems to be the restrictive factor. As a consequence, the demand of 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 been tested empirically yet. Most obvious is the potentially

positive impact of the damage on Demand Surge. More severe catastrophes lead to increasing costs and a stronger imbalance between demand and supply of 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 percent in Florida for the 2005 season compared to 24 percent if no hurricane had occurred in 2004. Therefore, it is necessary to explicitly consider alternative catastrophes in close temporal and spatial proximity. Hence, in compliance with the literature, we expect:

Proximity Catastrophe Hypothesis (H2):

The magnitude of the Demand Surge increases with other catastrophes in close temporal and spatial proximity.

If the total amount of claims per event rise, the procedure of insurance claims handling might suffer due to two reasons. First, politics might put pressure on insurance companies to settle claims quickly. As a consequence of this, claim adjusters spent less time for each assessment. Alternatively, insurance companies might install untrained claim adjusters. Both lead to a poorer damage assessment and typically to increased payments (Thomas, 1976). Secondly, in highly competitive markets, insurance companies may be classified by insured and by media according to the way they settled 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 regulate damages that are not attributable to the catastrophe itself due to fraud. Summarizing, both aspects lead to an increasing reconstruction demand. Although a part of the uninsured damage might be repaired too, the reconstruction work is normally distributed over a longer time period. Thus, we hypothesize:

Insurance Hypothesis (H3):

A higher 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. Hallegatte et al. (2008) show in a simulation study that the Demand Surge for the 2004/2005 hurricane season in Florida would have been much lower if the economy would have 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 growth stage of economy, Demand Surge levels are ceteris paribus higher.

A high number of establishments in the construction sector lead to competition and as a result keeps labor prices low (Olsen/Porter, 2011a). Moreover, capacity adjustments are more easily to conduct given an already high number of establishments in the construction sector, because both equipment and organizational structures are already available. Therefore, we suppose the contractor hypothesis.

Contractor Hypothesis (H5):

A higher number of contractors have a restraining effect on Demand Surge.

If the wage levels are already high due to a construction boom or a backlog from previous catastrophes, this might lessen further labor price increases which means that there could be saturation effects. With each further price increase of a single US Dollar, a growing number of workers is 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 towards a new equilibrium state. Hallegatte et al. (2008) observe a similar effect regarding structure losses. Their simulated Demand Surge level increases with growing losses but the slope decreases as losses become even bigger. Another reason for saturation effects might be that insurance policy limits are in case of an extended replacement cost coverage capped between 20 and 25 percent in excess of policy limit. As we 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 percent compared to a baseline scenario are thinkable. In this case, policyholders have to pay

these extra repair costs on their own and might delay further repairs, therefore reducing the overall demand. In a nutshell, we expect:

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 and finally, we present descriptive statistics of our data set.

3.1 Quantifying Demand Surge

3.1.1 Theoretical preliminary ideas 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:

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

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

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 base line 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 at hand. 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, i.e.:

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

Regarding the choice of t_{end} we will test different values as the date of the last settled claim is publicly not known. McCarty/Smith (2005) analyze the 2004 hurricane season in Florida and record 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. This might be a hint that a time slot of one year and a corresponding value of $t_{\text{end}} = 1$ might be too short for our purpose. However, catastrophe claims are generally considered to be short tailed (Harrington, 1997; Gron, 1994) and Gron (1994) states that during the years 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, $t_{\text{end}} = 3$ as an upper bound, and the choice of $t_{\text{end}} = 2$ is 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 the 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 measuring approach of 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 and finally, we subtract a base line price level in order to normalize the price evolution and to 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, which fulfill at least one of the following criteria: (1) 10 or more people reported killed; (2) 100 or more people reported 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 in by UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies (Scheuren et al., 2008). All dam-

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

age 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 comparability issues. Moreover, all these values refer to the direct damage (Scheuren et al., 2008). Thus, indirect damages, i.e. the reduction of the total value added, are not contained (Hallegatte/Przyluski, 2010). As small catastrophes are less likely to produce an increasing labor demand that results in Demand Surge effects, we use a cut-off value of 100 million US dollars for events to be entered 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 publishes a retail labor index on a quarterly basis since 2002 and on a monthly basis since 2009 for each of these areas (Xactware, 2011). Obviously, the localizations in EM-DAT are usually not consistent with Xactware data. As 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 for each of them the closest Xactware localization available (shortest distance of two points on a surface of a sphere). Then, we retrieve the corresponding retail labor index time series for this Xactware localization.

To measure the relative price increase due to the 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 had no catastrophe occurred. 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 3 years and use the result as our Demand Surge measure. An exemplary calculation is shown in Figure 3.

[Figure 3]

3.2 Demand Surge Drivers

For the direct damage caused by the catastrophes, we rely on data of the EM-DAT database. Though, 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 the single catastrophe regions. For the 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. Up to date 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 like Cat Bonds. On the federal state level, direct damages are allocated according to their relative share of estimated insurance payments. On the city/county level in turn, these partial damages are uniformly distributed across all localizations. As 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 in close temporal and spatial proximity, we additionally calculate direct damages in a given radius of 450 km including direct damages in the same federal 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 and could observe that radii of up to 450 km had a significant effect on Demand Surge, whereas damages in 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 in 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 2002-2010.

In order 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. Therefore 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 end of the catastrophe. For this purpose we use data of the Bureau of Economic Analyses (BEA), which provide material on an annual basis for each federal state in the US.

To reflect the supply side of the labor market, we measure the capacity of the construction sector indicated by the number of establishments. This data was retrieved from the Quarterly Census of Employment and Wages (QCEW) which is compiled by the Bureau of Labor Statistics. Data are quarterly available for each county, metropolitan statistical area (MSA) or federal state within the US.

Finally, possible repletion effects are measured by the relative change of the retail labor index of the catastrophe region in the foregoing 18 months before the end of 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.

[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 noteworthy that the number of observations is quite uniformly distributed across years except from the unexpectedly high value in 2008. Whereas total losses in 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 a damage of less or equal to 100 million US-\$, only 188 of 963 entries remain. The distribution of the damage is highly right skewed with a mean value of 1.576 billion US-\$, a median of 0.2445 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 per-

cent of all cases, at least one further catastrophe can be observed in each time slot. Moreover, we find that the GDP change is in more than 75 percent of the cases negative, which indicates that at the time the catastrophes took place the construction sector probably had idle capacities. The maximum wage change of 49.11 percent 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 that it is likely that the current wage level is already highly driven by Demand Surge from previous events. In matters of the Mapping distance a perfect matching could be achieved in 86 percent of the cases. In Table 4b the number of observations is further limited. The sample now comprises 57 catastrophe regions with a minimum sustained damage of 500 million US-\$. As a consequence of this, the mean value of the damage variable is significantly higher with 4.708 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 represented 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 bigger 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 and 1.9 percent, whereas the Demand Surge effect for extreme catastrophes is more pronounced. In this case the mean Demand Surge effect varies between 2.7 and 4.6 percent. The fact that the maxima remain the same both for large and extreme catastrophes points to the corollary that high Demand Surge effects correspond with high damages.

Finally, in Table 6 the pairwise correlations between the above described variables are presented.

[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 condition on Demand Surge. According to section 3, we consider catastrophe events with a damage of at least 100 million US-\$ because it is unlikely that rather small events lead to a significantly increasing demand of building services and, thus, to increasing prices. We analyze the resulting 176 observations using OLS regressions; 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 occurred in the same region and 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 hypotheses (H1)* and the *proximity catastrophe hypotheses (H2)*. To be more specific, the prices of retail labor increase by about 1.5% if the damage 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 year also lead to a significantly higher Demand Surge. Whereas the coefficients regarding these time periods are each highly significant with $p < 0.1\%$, catastrophes that occurred before or after this period do not significantly increase the Demand Surge effect. This indicates that in the latter situation most of the repair work has already been finished when the new event occurs, so that the events can be treated as independent when determining the Demand Surge effect. This is generally in line with the finding that catastrophe insurance is short tailed, i.e. homeowners' claims after catastrophes are usually paid quite promptly (Harrington, 1997).

In model (A.2), we additionally include the number of insurance claims of the catastrophe. We find that a high number of claims leads to a significantly higher Demand Surge. At the same time, the coefficient of total damage is reduced slightly. The reason is that a high number of claims usually comes along with a high total damage. However, as both variables are considered in (A.2), the number of claims does not represent the damage amount so that the positive coefficient rather indicates that there is a higher chance that insurance claims are regulated 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 regulate claims from politics and 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 the macroeconomic data are not available for the exact catastrophe location. However, the variable is not significant showing that the 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. The effect is not only statistically significant with $p < 0.1\%$ but also the economic effect is substantial: If the GDP increased by 1% before the catastrophe, we observe a Demand Surge effect of approximately 0.25%. This confirms the *growth hypothesis (H4)*, which states that Demand Surge is more pronounced if the construction sector is in a growth stage so that 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 are several reasons for saturation effects of 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 model (A.5), we analyze if there is a differing Demand Surge effect of tail events. As stated above, it is reasonable to assume that Demand Surge effect is only relevant for large catastrophe events; thus, we only considered catastrophes with damage of more than 100 million US-\$. However, ex ante it is unclear, which barrier might be appropriate. Moreover, the relation between damage and Demand Surge could be non-linear. Against this background, we include a dummy variable for tail events with a damage of more than 1 billion US-\$. Indeed, the dummy variable is significantly positive which implies that Demand Surge is even more pronounced for tail events than implied by the linear effect that is considered in model (A.1)–(A.4). As consequence, the coefficient of the variable total damage decreases. However, the linear effect of total damage remains highly significant and the other effects are largely unchanged, too. Thus, the general findings described before remain valid.

Summing up, most effects are very stable in terms of statistical significance and absolute size. Our results suggest that the hypotheses H1–H5 are true. On the contrary, a cost increase

of building services in a period before the catastrophe does not lead to a significant reduction of Demand Surge so that we cannot confirm the hypothesis H6. However, it may be possible that saturation are only relevant for even more severe catastrophe events. Furthermore, the adjusted R^2 of up to 0.778 shows that Demand Surge can be attributed to the considered effects to large extent.

4.2 Demand Surge Effect for Extreme Catastrophes

As mentioned above, the restriction to events with damage of more than 100 million US-\$ is somewhat arbitrary. The results of model (A.5) of section 4.1 suggest that Demand Surge does not linearly increase with damage but the effect is stronger for tail events. To study this effect further, we subsequently constrain the data set to events with damage of more than 500 million US-\$. Due to the higher bound, the number of observations significantly decreases from 175 to 53. 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 variable wage change, even if we did not find the saturation effect to be significant. As a saturation effect is most likely for catastrophes with very high damages, it is reasonable that this effect can only be observed 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.5) to allow an easier comparison of the results. Model (B.2) presents the effect of the total damage of the considered catastrophe and the damage of other catastrophes that occurred in a period of up to 0.5 years before or up to 1.5 years after the particular event in a nearby region. In model (B.3), we additionally include the other variables where we found the coefficients to be significant on the larger data set in most specifications; in addition, we include the variable wage change to account for saturation effects. We find that almost all of the considered variables remain statistically significant on the subsample of extreme events. Moreover, the coefficients of most considered variables have a similar magnitude as on 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.

Though, 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% leads to a reduction of the Demand Surge effect of 1.7%. Thus, for extreme catastrophes, saturation effects cause that Demand Surge is indeed less pronounced, which confirms the *saturation hypothesis (H6)*. Furthermore, the dummy variable for tail events with damage of more than 1 billion US-\$ is no longer significant suggesting that there is no relevant difference between the Demand Surge effect of events with damage of more than 500 million and 1 billion US-\$.

Summing up, for extreme catastrophes with damage of more than 500 million US-\$, all hypothesis H1–H6 can be confirmed. Moreover, the adjusted R^2 of 0.861 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 section 4.1 and 4.2, we have 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 the chosen period 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, about 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 152 if we consider all events with damage of more than 100 million US-\$ (instead of 176 observations for the 2-year period). Model (C.1) and (C.2) contain the results for catastrophes with a damage of more than 100 million US-\$; model (C.3) and (C.4) refer to the subset of extreme catastrophes with a damage of more than 500 million US-\$. We find that the results are very similar to those of sec-

tion 4.1 and 4.2, in terms of both statistical significance and the magnitude of the effects. An exception is the number of claims, which is no longer significant. Moreover, the coefficients of the additional variables for catastrophes that occurred in the period 2 to 3 years before or after the considered event are not significantly different from zero, which supports that a 2-year period might be appropriate. However, the adjusted R^2 of these models are even slightly higher than before, with values of 0.808 instead of 0.778 for the larger sample and 0.895 instead of 0.861 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 188 instead of 176 available observations. We find that most 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. This 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. Though, 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 done 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 rather leads to an underestimation of the total costs. Against this background, we alternatively compute the *maximum* Demand Surge effect within 2 years after a catastrophe. However, as not the entire repair work is done at the time of maximum Demand Surge, this rather leads to an overestimation of the increase of 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 section 4.1 and 4.2, apart from the fact that the magnitude of Demand Surge is larger, which is obviously 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 higher number of establishments in the construction sector as well as a preceding wage increase for building services lead to a less pronounced Demand Surge. Thus, hypotheses H1, H2, H5, and H6 are supported by the results for the maximum Demand Surge effect. The coefficient of the number of claims, though, is not significant, and a growth stage of the construction sector has only a significant effect on Demand Surge if we analyze the larger data set (model (D.2)). 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 H3 and H4 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 more clarity.

[Table 11]

5 Conclusion and Implications

In this paper, we provide an extensive econometric analysis of the Demand Surge effect and we achieve a model in which we identify the most important determinants of Demand Surge. This model is able to explain more than 75 % of variance of the Demand Surge effect. According to the model, highly relevant drivers of Demand Surge are the amount of loss of a catastrophe and further catastrophes that occur in proximity of time in the same region. In concrete terms, a damage increase of 10 billion US-\$ leads to a price increase of retail labor of about 1.5%. In addition, further catastrophes that occur in the same region during 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 regulated insurance claims of a catastrophe and the Demand Surge effect. Because a higher number of claims usually results from a higher total damage, the consideration of these both variables in the model indicates that the regulation policy of the insurers is less restrictive if the total

number of claims is high. Furthermore, we see a positive relationship between GDP of the construction sector and Demand Surge. If GDP increases by 1% before a catastrophe, we identify a Demand Surge effect of 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 higher number of establishments implies a higher ability to adjust the capacity in the construction sector. In addition, if we restrict the data to damages of more than 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 significant if we also consider smaller catastrophes because a saturation effect is most likely for catastrophes with very high damages.

Our results have important implications for insurance companies, governments, issuers and investors of catastrophe-linked securities, and building companies. 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 or solvency of the insurance company.

The consideration and the comprehension of Demand Surge is also relevant for governments to ensure adequate catastrophe precautions and appropriate price regulations in the construction sector. Price regulations are e.g. conceivable to restrict price increases after a catastrophe. 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 and the corresponding price increase have 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 (Hallegatte et al., 2008; Hallegatte, 2008).

Issuers and investors of catastrophe-linked securities have, on the one hand, to determine the risk profile of catastrophe losses. On the other hand, they have to assess price reactions of insurance stocks after catastrophes (Gangopadhyay et al., 2010; Lamb, 1995; Marlett et al., 2000; Shelor et al., 1992). For both components an appropriate assessment of the Demand Surge effect is of high relevance.

Finally, also building companies should have great interest in the Demand Surge effect 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.

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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 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	

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Table 2: Variable definitions

Variable	Definition
Damage	Total damage of the catastrophe (in billions of US-\$).
Subsequent damage (a; b)	Total damage of subsequent catastrophes that occurred in geographical and temporal proximity (in billions of US-\$); (a, b) denominates the time period in years with respect to the considered event.
Previous damage [a; b)	Total damage of previous catastrophes that occurred in geographical and temporal proximity (in billions of 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 federal state.
Establishments	Number of establishments of the construction industry in the affected county/federal state (in thousands).
Wage change	Relative change of wage in the construction sector during the 18 months before the catastrophe.
Tail events	Dummy variable that equals 1 if damage > US-\$1 billion.
Mapping distance	Distance between the catastrophe (data from EM-DAT) and the assigned localization of economic variables (data from Xactware) (in km).

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Table 3: Summary statistics - composition of the data set

	Obs.	Percentage
<i>Panel A: Year</i>		
2002	13	6.91
2003	19	10.11
2004	19	10.11
2005	16	8.51
2006	18	9.57
2007	22	11.70
2008	45	23.94
2009	24	12.77
2010	12	6.38
<i>Panel B: Type of disaster</i>		
Flood	23	12.23
Storm	156	82.98
Local Storm	95	50.53
Tropical Cyclone	46	24.47
Extratropical Cyclone (Winter Storm)	2	1.06
Not further specified	13	6.91
Wildfire	9	4.79

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

The sample comprises 188 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)	188	1.576	5.139	0.1020	0.1520	0.2445	0.5892	41.01
Subsequent damage (0; 0.5]	188	1.640	8.536	0	0	0.0665	0.3508	110.99
Subsequent damage (0.5; 1]	188	0.9966	5.036	0	0	0.0385	0.2210	57.34
Subsequent damage (1; 1.5]	188	0.8213	2.721	0	0	0.0516	0.4143	21.90
Subsequent damage (1.5; 2]	188	0.3619	1.165	0	0	0.0667	0.2247	10.26
Subsequent damage (2; 3]	188	1.883	6.536	0	0	0.1955	0.6078	62.48
Previous damage [0.5; 0)	188	1.096	5.024	0	0	0.0440	0.2361	57.34
Previous damage [1; 0.5)	188	0.8571	3.998	0	0	0.0795	0.2396	32.57
Previous damage [1.5; 1)	188	0.3549	2.255	0	0	0.0549	0.1818	30.23
Previous damage [2; 1.5)	188	0.3846	2.501	0	0	0.0082	0.1031	32.57
Previous damage [3; 2)	188	1.171	5.018	0	0.0396	0.1764	0.4332	62.48
Claims (millions)	188	0.2710	0.3694	0.0028	0.0555	0.1300	0.2812	1.385
GDP change	188	-0.0385	0.0453	-0.2074	-0.0634	-0.0343	-0.0085	0.0630
Establishments ('000)	188	18.76	15.95	0.050	8.161	12.07	26.68	79.90
Wage change	187	0.0864	0.0630	0.0036	0.0518	0.0734	0.0997	0.4911
Mapping distance (km)	188	4.592	14.45	0	0	0	0	84.19

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

The sample comprises 57 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)	57	4.708	8.701	0.5035	0.6777	1.587	4.558	41.01
Subsequent damage (0; 0.5]	57	2.110	4.417	0	0	0.2066	1.7508	21.90
Subsequent damage (0.5; 1]	57	1.587	4.924	0	0	0.0439	0.5227	32.57
Subsequent damage (1; 1.5]	57	1.717	4.671	0	0	0	0.1805	21.90
Subsequent damage (1.5; 2]	57	0.1171	0.2547	0	0	0	0.1220	1.574
Subsequent damage (2; 3]	57	0.8476	2.919	0	0.0748	0.1497	0.4979	21.42
Previous damage [0.5; 0)	57	2.055	4.796	0	0	0.1664	1.096	16.28
Previous damage [1; 0.5)	57	1.535	5.731	0	0	0.1171	0.3538	30.23
Previous damage [1.5; 1)	57	0.7308	3.997	0	0.0018	0.1033	0.1719	30.23
Previous damage [2; 1.5)	57	0.1769	0.7193	0	0	0.0071	0.0692	5.140
Previous damage [3; 2)	57	0.7833	1.582	0	0	0.1713	0.4332	5.617
Claims (millions)	57	0.4814	0.4888	0.0180	0.0870	0.271	0.6042	1.385
GDP change	57	-0.0297	0.0557	-0.2074	-0.0634	-0.0310	-0.0057	0.0630
Establishments ('000)	57	20.25	18.03	0.05	8.552	11.73	26.88	67.13
Wage change	57	0.1052	0.0941	0.0036	0.0578	0.0760	0.1048	0.4911
Mapping distance (km)	57	6.272	15.41	0	0	0	0	80.35

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Table 5: Summary statistics – Demand Surge

The table shows descriptive statistics of 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 more than 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	188	0.0096	0.0332	-0.0419	-0.0072	0.0009	0.0105	0.2190
Avg. Demand Surge: 2 years	176	0.0136	0.0480	-0.0666	-0.0117	0.0015	0.0177	0.3119
Avg. Demand Surge: 3 years	152	0.0185	0.0594	-0.0776	-0.0125	0.0077	0.0280	0.3466
Max. Demand Surge: 2 years	176	0.0330	0.0665	-0.0119	-0.0001	0.0125	0.0406	0.4449
<i>Panel B: Extreme catastrophes (damage > \$500 million)</i>								
Avg. Demand Surge: 1 year	57	0.0268	0.0516	-0.0171	-0.0047	0.0030	0.0365	0.2190
Avg. Demand Surge: 2 years	53	0.0366	0.0744	-0.0236	-0.0058	0.0102	0.0383	0.3119
Avg. Demand Surge: 3 years	46	0.0460	0.0907	-0.0335	-0.0075	0.0158	0.0434	0.3466
Max. Demand Surge: 2 years	53	0.0629	0.1050	-0.0068	0.0002	0.0270	0.0615	0.4449

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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	0.18	1.00			
Establishments	0.02	-0.07	-0.04	0.02	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

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Table 7: Demand Surge for large catastrophes

The table reports results of OLS regressions 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)	(A.5)
Damage	0.0022*** (6.02)	0.0017*** (4.06)	0.0016*** (4.12)	0.0017*** (4.15)	0.0013** (2.95)
Subsequent damage (0; 0.5]	0.0012*** (5.45)	0.0012*** (5.52)	0.0012*** (5.58)	0.0012*** (5.60)	0.0012*** (5.80)
Subsequent damage (0.5; 1]	0.0016*** (4.28)	0.0015*** (4.02)	0.0013*** (3.78)	0.0013*** (3.59)	0.0012*** (3.49)
Subsequent damage (1; 1.5]	0.0092*** (12.00)	0.0094*** (12.43)	0.0088*** (11.36)	0.0085*** (10.23)	0.0080*** (9.81)
Subsequent damage (1.5; 2]	-0.0003 (-0.16)	0.0002 (0.14)	0.0009 (0.60)	0.0007 (0.43)	0.0009 (0.58)
Previous damage [0.5; 0)	0.0021*** (5.49)	0.0021*** (5.49)	0.0019*** (5.39)	0.0020*** (5.45)	0.0019*** (5.31)
Previous damage [1; 0.5)	-0.0002 (-0.43)	-0.0003 (-0.63)	-0.0007 (-1.38)	-0.0004 (-0.64)	-0.0005 (-0.86)
Previous damage [1.5; 1)	-0.0009 (-1.06)	-0.0010 (-1.22)	-0.0020* (-2.47)	-0.0014 (-1.50)	-0.0016† (-1.72)
Previous damage [2; 1.5)	-0.0007 (-0.90)	-0.0006 (-0.76)	-0.0007 (-1.07)	-0.0007 (-1.07)	-0.0007 (-1.01)
Claims		0.0152*** (2.64)	0.0137* (2.56)	0.0140* (2.59)	0.0095† (1.74)
GDP change			0.2436*** (4.57)	0.2503*** (4.60)	0.2473*** (4.67)
Establishments			-0.0003* (-2.22)	-0.0003* (-2.17)	-0.0003* (-2.42)
Wage change				-0.0461 (-0.95)	-0.0611 (-1.29)
Tail events					0.0192** (3.19)
Mapping distance		0.0001 (0.90)	-0.0000 (-0.35)	-0.0001 (-0.39)	-0.0001 (-0.58)
Constant	-0.0033 (-1.46)	-0.0073** (-2.77)	0.0085* (2.11)	0.0123* (2.18)	0.0134* (2.44)
Observations	176	176	176	175	175
Adjusted R ²	0.721	0.731	0.766	0.766	0.778

Table 8: Demand Surge for extreme catastrophes

The table reports results of OLS regressions 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	0.0013** (2.95)	0.0015** (2.70)	0.0011 [†] (1.88)
Subsequent damage (0; 0.5]	0.0012*** (5.80)	0.0023 [†] (1.82)	0.0045** (3.15)
Subsequent damage (0.5; 1]	0.0012*** (3.49)	0.0026** (2.73)	0.0015 [†] (1.75)
Subsequent damage (1; 1.5]	0.0080*** (9.81)	0.0078*** (6.01)	0.0063*** (4.64)
Subsequent damage (1.5; 2]	0.0009 (0.58)		
Previous damage [0.5; 0)	0.0019*** (5.31)	0.0034** (2.90)	0.0035** (3.39)
Previous damage [1; 0.5)	-0.0005 (-0.86)		
Previous damage [1.5; 1)	-0.0016 [†] (-1.72)		
Previous damage [2; 1.5)	-0.0007 (-1.01)		
Claims	0.0095 [†] (1.74)		0.0182 [†] (1.93)
GDP change	0.2473*** (4.67)		0.2092 [†] (1.81)
Establishments	-0.0003* (-2.42)		-0.0006* (-2.38)
Wage change	-0.0611 (-1.29)		-0.1700** (-2.85)
Tail events	0.0192** (3.19)	0.0152 (1.38)	0.0137 (1.42)
Mapping distance	-0.0001 (-0.58)		
Constant	0.0134* (2.44)	-0.0109 (-1.55)	0.0191 [†] (1.71)
Observations	175	53	53
Adjusted R ²	0.778	0.807	0.861

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Table 9: 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. Model (C.1) and (C.2) refer to catastrophes with total damage of at least 100 million US-\$, whereas the relevant barrier for model (C.3) and (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 > 100 mio. \$		Damage > 500 mio. \$	
	(C.1)	(C.2)	(C.3)	(C.4)
Damage	0.0022*** (5.08)	0.0014** (2.80)	0.0015* (2.53)	0.0014* (2.26)
Subsequent damage (0; 0.5]	0.0015*** (5.54)	0.0015*** (6.01)	0.0024 [†] (1.72)	0.0043* (2.72)
Subsequent damage (0.5; 1]	0.0021*** (4.57)	0.0016*** (3.99)	0.0029** (2.81)	0.0015 (1.65)
Subsequent damage (1; 1.5]	0.0110** (12.00)	0.0090** (9.13)	0.0093*** (6.57)	0.0072*** (4.72)
Subsequent damage (1.5; 2]	-0.0007 (-0.28)	0.0016 (0.70)		
Subsequent damage (2; 3]	0.0006 (1.63)	0.0004 (1.36)		
Previous damage [0.5; 0)	0.0025*** (5.29)	0.0023*** (5.28)	0.0047** (3.54)	0.0045*** (3.77)
Previous damage [1; 0.5)	-0.0002 (-0.42)	-0.0009 (-1.29)		
Previous damage [1.5; 1)	-0.0012 (-1.17)	-0.0024* (-2.14)		
Previous damage [2; 1.5)	-0.0006 (-0.72)	-0.0008 (-1.01)		
Previous damage [3; 2)	-0.0001 (-0.23)	-0.0003 (-0.65)		
Claims		0.0060 (0.95)		0.0109 (1.07)
GDP change		0.4267*** (6.01)		0.3312* (2.31)
Establishments		-0.0003 [†] (-1.79)		-0.0006 [†] (-1.85)
Wage change		-0.0788 (-1.39)		-0.2160** (-3.29)
Tail events		0.0203** (2.85)	0.0177 (1.39)	0.0175 (1.59)
Mapping distance		-0.0001 (-0.84)		
Constant	-0.0043 (-1.39)	0.0215** (3.02)	-0.0150 [†] (-1.69)	0.0264 [†] (1.91)
Observations	152	152	46	46
Adjusted R ²	0.741	0.808	0.850	0.895

Table 10: 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. Model (C.1) and (C.2) refer to catastrophes with total damage of at least 100 million US-\$, whereas the relevant barrier for model (C.3) and (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 > 100 mio. \$		Damage > 500 mio. \$	
	(D.1)	(D.2)	(D.3)	(D.4)
Damage	0.0024*** (6.83)	0.0017*** (4.56)	0.0013* (2.28)	0.0011* (2.22)
Subsequent damage (0; 0.5]	0.0009*** (4.32)	0.0010*** (5.33)	0.0038** (3.41)	0.0047*** (4.00)
Subsequent damage (0.5; 1]	0.0016*** (4.47)	0.0008* (2.59)	0.0021* (2.22)	0.0003 (0.45)
Previous damage [0.5; 0)	0.0025*** (6.99)	0.0022*** (7.16)	0.0045*** (4.46)	0.0039*** (4.62)
Previous damage [1; 0.5)	-0.0004 (-0.84)	-0.0001 (-0.15)		
Claims		0.0074 (1.53)		0.0171* (2.04)
GDP change		0.2345*** (6.27)		0.2473** (2.98)
Establishments		0.0000 (0.38)		-0.0004 (-1.55)
Wage change		-0.1824*** (-5.68)		-0.2430*** (-5.49)
Tail events		0.0224*** (4.46)	0.0061 (0.60)	0.0112 (1.35)
Mapping distance		-0.0000 (-0.14)		
Constant	0.0003 (0.17)	0.0203*** (4.58)	-0.0033 (-0.50)	0.0288** (3.07)
Observations	188	187	57	57
Adjusted R ²	0.458	0.622	0.607	0.766

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Table 11: 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. Model (E.1) and (E.2) refer to catastrophes with total damage of at least 100 million US-\$, whereas the relevant barrier for model (E.3) and (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 > 100 mio. \$		Damage > 500 mio. \$	
	(E.1)	(E.2)	(E.3)	(E.4)
Damage	0.0026*** (5.72)	0.0015** (2.82)	0.0018* (2.43)	0.0010 (1.33)
Subsequent damage (0; 0.5]	0.0021*** (7.40)	0.0021*** (7.88)	0.0028 (1.61)	0.0064** (3.43)
Subsequent damage (0.5; 1]	0.0028** (5.83)	0.0023*** (5.12)	0.0037** (2.90)	0.0024* (2.10)
Subsequent damage (1; 1.5]	0.0132*** (13.83)	0.0118*** (11.34)	0.0116*** (6.64)	0.0102*** (5.69)
Subsequent damage (1.5; 2]	0.0000 (0.01)	0.0012 (0.62)		
Previous damage [0.5; 0)	0.0026*** (5.38)	0.0024*** (5.30)	0.0051** (3.28)	0.0052*** (3.79)
Previous damage [1; 0.5)	-0.0005 (-0.88)	-0.0005 (-0.76)		
Previous damage [1.5; 1)	-0.0008 (-0.80)	-0.0012 (-1.00)		
Previous damage [2; 1.5)	-0.0007 (-0.80)	-0.0007 (-0.85)		
Claims		0.0104 (1.51)		0.0202 (1.63)
GDP change		0.2649*** (3.95)		0.2020 (1.33)
Establishments		-0.0004* (-2.27)		-0.0012** (-3.37)
Wage change		-0.1099† (-1.83)		-0.1916* (-2.44)
Tail events		0.0259*** (3.40)	0.0213 (1.45)	0.0190 (1.49)
Mapping distance		0.0000 (0.01)		
Constant	0.0090** (3.18)	0.0300*** (4.31)	-0.0032 (-0.34)	0.0385* (2.62)
Observations	176	175	53	53
Adjusted R ²	0.772	0.815	0.826	0.879

Figure 1: Retail Labor Price Index

The figure shows the price evolution of the retail labor price index contained in Xactware, a member of the Verisk Insurance Solutions Group, for West Palm Beach, Florida and the entire US.

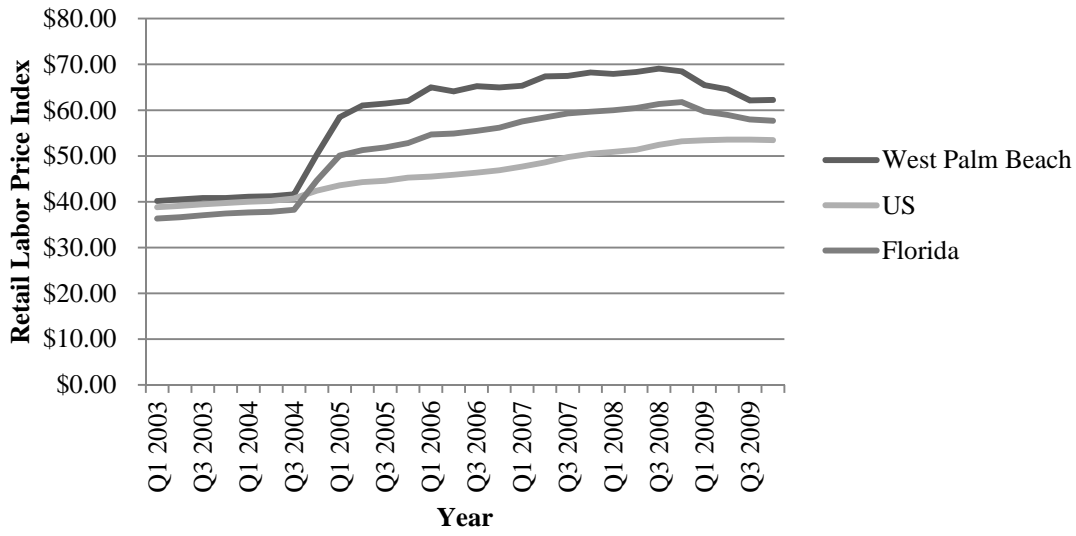


Figure 2: Building Material Price Index

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

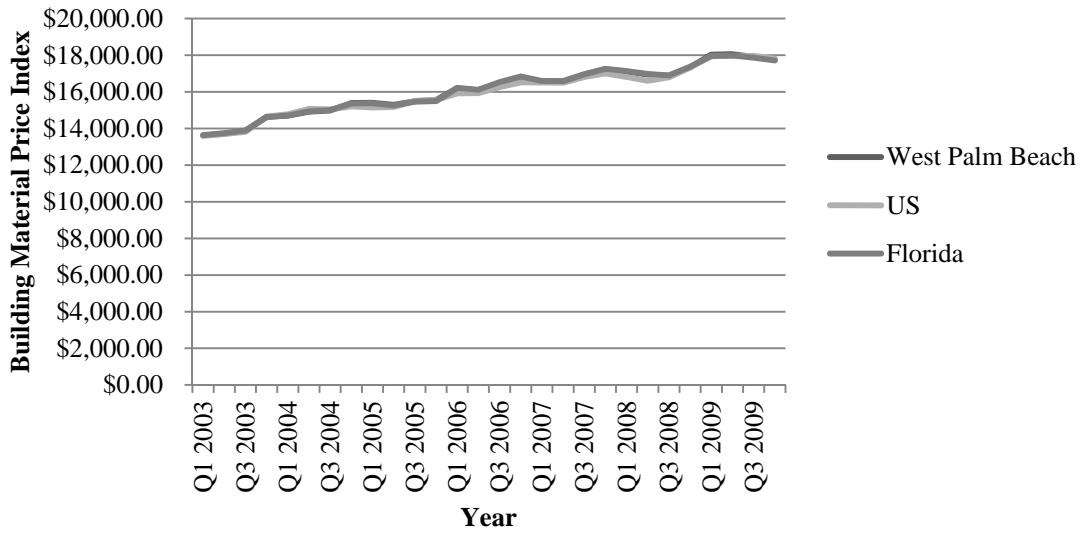


Figure 3: Demand Surge Measurement

In this figure the 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, only the mean value of $p(t)$ over differing time periods of 1, 2 or 3 years has to be calculated.

