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Insured Loss Inflation: How Natural Catastrophes Affect Reconstruction Costs

David Döhrmann
Marc Gürtler
Martin Hibbeln

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 192 catastrophe events in the United States. Our model explains more than 75 percent of the variance of the Demand Surge effect and is thus able to identify the key drivers of the phenomenon.

Introduction

In recent decades, dramatic increases in the number and severity of catastrophes have been observed (Kunreuther and 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).

David Döhrmann is at Deutsche Bundesbank, Markets Department, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main, Germany. Marc Gürtler is at Braunschweig Institute of Technology, Department of Finance, Abt-Jerusalem-Str. 7, 38106 Braunschweig, Germany. Martin Hibbeln (contact author) is at University of Duisburg-Essen, Mercator School of Management, Lotharstr. 65, 47057 Duisburg, Germany. Hibbeln can be contacted via e-mail: martin.hibbeln@uni-due.de. We would like to thank an anonymous referee, Keith J. Crocker (the editor), Randy Dumm, Lorilee Medders, and Richard Sylves, as well as the participants of the 2013 Annual Meeting of the American Risk and Insurance Association, the 2013 Annual Congress of the German Insurance Science Association, and the 2013 Annual Meeting of the German Finance Association for helpful comments. The article represents the authors' personal opinions and do not necessarily reflect the views of the Deutsche Bundesbank or its staff. David Döhrmann acknowledges the financial support from the German Research Foundation (DFG) and the German Insurance Science Association (DVfVW).

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 reconstruction labor and building materials. 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 an inflation of insured losses. For example, it is estimated that the average Demand Surge effect for the affected construction lines due to Hurricane Katrina is in the range of 30–40 percent (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 and Porter, 2011a). Though the scientific literature considers Demand Surge exclusively on a qualitative level or only for a specific catastrophe type or event, universally valid quantitative models for Demand Surge have not been published. In contrast, the 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. Even if some background material is available to customers that provides some intuition about the Demand Surge models of these companies, information about the models is neither publicly available nor is it clear which concrete empirical analyses or results underlie their models.

Against this background, the present article 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 article provides a basis for the quantitative assessment of Demand Surge for future catastrophes, which, on one hand, is important for (public and private) 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 data set 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 United States and Canada since 2002. Our proposed Demand Surge model is able to explain more than

75 percent 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. The reason might be that if the total number of claims is large, the regulation policy of insurers is less restrictive. As a timely reconstruction is more likely if the damage is insured, this leads to an increased reconstruction demand after the catastrophe and, thus, to a higher Demand Surge effect. 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 employees in the construction sector leads to a decreasing Demand Surge effect because, in this situation, the construction industry can more easily cope with the sudden increase in demand. Moreover, 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 article is structured as follows. In the "Hypotheses Development" section, 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 the "Modeling of Demand Surge and Data" section, we develop a measure for Demand Surge and explain the relevant exogenous variables of the model. Furthermore, we report descriptive statistics of the data set. In the "Empirical Analyses" section, we conduct an event study and discuss the empirical analyses and related robustness checks. In the "Conclusions and Implications" section, we present our conclusions.

HYPOTHESES DEVELOPMENT

Literature Review

Only two decades ago, researchers started to develop models to describe Demand Surge (Olsen and Porter, 2010). Leading among them are models developed by the three main catastrophe modeling companies, AIR, 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 and 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 and 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 52 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 (Hallegatte, 2008; Florida International University, 2009). 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 as price increases in the construction sector for building products and services. Based on simulations, a Demand Surge effect of 13 percent is calculated, but the most important result is nonlinearity between direct losses and total economic losses.

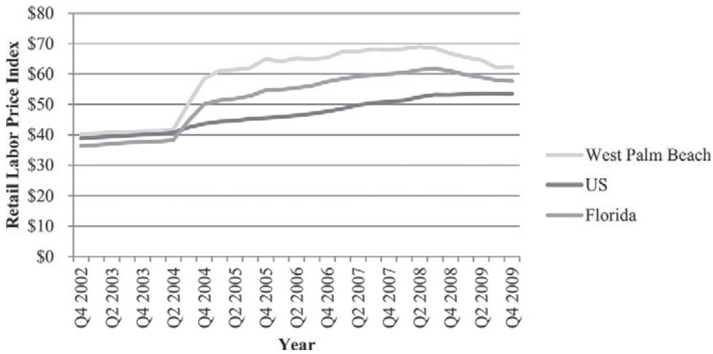
Impact on Labor and Material Prices

When dealing with 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 United States from Q4 2002 to Q4 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.

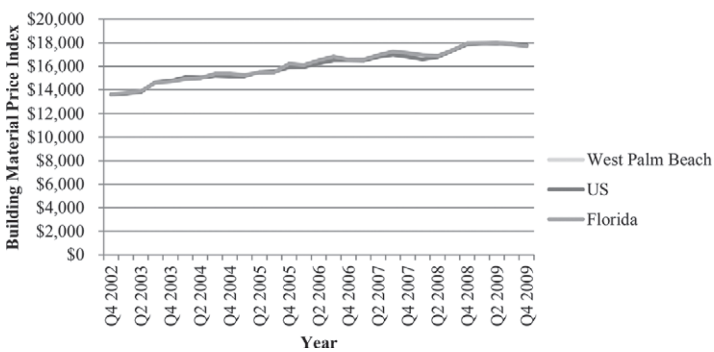
In summary, typically, labor capacity seems to be the restrictive factor. As a consequence, the demand for building materials is distributed over a longer time

Figure 1
Retail Labor Price Index



Note: The figure shows the price evolution of the retail labor price index for West Palm Beach (Florida), Florida, and the entire United States.

Figure 2
Building Material Price Index



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

period. Moreover, this additional demand is predictable to some extent. Thus, the production capacity can be adapted to the change in demand, and the impact on material prices is less pronounced. This finding is supported by work conducted by Olsen and Porter (2011b) and AIR (2009). Olsen and Porter, for example, show that correlation between wind speed, as a proxy for damage, and material prices is low.

Hypotheses

In the literature, common themes of Demand Surge are discussed (Hallegatte et al., 2008; Olsen and 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 and 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 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 several 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).[1] Second, 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 and Porter, 2010). For example, Risk Management Solutions (2000) states that insurance companies were overwhelmed by nearly 3 million claims in the aftermath of the 1999 Windstorms Lothar and Martin in France. In response some insurers applied a threshold of €7,620 (US$7,725) for claims to be verified.[2] As a consequence, insurance companies might settle claims that are not attributable to the catastrophe itself due to fraud. Third, given the damage

[1]There is anecdotal evidence that many homeowners are willing to accept a lower settlement price than what they could have received in order to get a check from their insurers, which leads to *reduced* insurance payments. However, while being relevant for insurers and insured, such reduced payments are not induced by the number of insurance claims. Rather, this leads to, on average, smaller payments for every insurance claim, independent of the number of claims. Thus, the hypothesis is unaffected.

[2]Since 1982 the CAT/NAT is the French insurance regime to manage recovery costs after natural disasters. This mixed system is relying on both the state and the insurance industry. Insurance contracts that insure damages to property must also cover against damages due to natural disasters. In return, the insured must pay an additional premium set by the French state, which is independent of the risk exposure. The average additional premium for the CAT/NAT guarantee is approximately €25 per year for dwellings. Thus, most of the property damages caused by Windstorms Lothar and Martin in France were insured (Raspiller, 2012).

incurred by the catastrophe is insured, the homeowner may not be inclined to request the cheapest quotation possible for the reconstruction. Rather, he is interested in getting his damage repaired as fast as possible regardless of the price. In summary, all of these aspects lead to increasing reconstruction costs. 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 leads 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. This view is supported by Hallegatte and Ghil (2007). Against this background, we expect the following:

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

A larger number of employees in the construction sector leads to higher competition and, consequently, keeps labor prices low (Olsen and Porter, 2011a). Moreover, it is more likely that the construction industry is capable of dealing with the sudden reconstruction demand given an already high number of employees. Therefore, we propose the following:

Employee Hypothesis (H5): *A larger number of employees in the construction sector has 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 U.S. 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 temporarily 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 percent in excess of the policy limit. As already mentioned in the "Impact on Labor and Material Prices" section, 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 20–25 percent 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.*

MODELING OF DEMAND SURGE AND DATA

Subsequently, we first describe the construction of our measure of the Demand Surge effect. In a second step, we show how insurance companies are affected by Demand Surge. Third, we explain the measurement of relevant exogenous variables. Lastly, we present descriptive statistics of our data set.

Quantifying Demand Surge

Theoretical Consideration of Demand Surge. We examine catastrophe-related payments for reconstruction, resulting from the demand quantities of building services and their prices. As already mentioned, the present study focuses on reconstruction labor costs as discussed in the "Impact on Labor and Material Prices" section. We consider a continuous time model with points in time $t \in [0, t_{\text{end}}]$, where $t = 0$ denotes the point in time of the occurrence of the catastrophe and t_{end} is the point in time of the last damage repair. Furthermore, $x(t)$ denotes the density of the (realized) demand quantity of reconstruction labor at time t with

$$\int_{t=0}^{t_{\text{end}}} x(t)\mathrm{dt} = 1. \tag{1}$$

$P_{\text{cat}}(t)$ and $P_{\text{no-cat}}(t)$ characterize the levels of reconstruction labor costs in the observed catastrophe scenario and a "normal" no-catastrophe scenario, respectively. However, in order to make different regions comparable, we do not consider absolute prices $P(t)$ for reconstruction labor but rather a normalized price index $P(t)/P(0)$. Against this background, we define

$$\text{Avg. Demand Surge} = \int_{t=0}^{t_{\text{end}}} \frac{P_{\text{cat}}(t)}{P_{\text{cat}}(0)} \cdot x(t)dt - \int_{t=0}^{t_{\text{end}}} \frac{P_{\text{no-cat}}(t)}{P_{\text{no-cat}}(0)} \cdot x(t)\mathrm{dt} \tag{2}$$

as the (weighted) average change of reconstruction labor costs based on the price index over the time interval $[0, t_{\text{end}}]$ when switching from a no-catastrophe to a catastrophe price level. To simplify the calculation for the upcoming empirical analysis, we assume a uniform distribution of the demand quantity of reconstruction labor over time:[3]

$$x(t) = \frac{1}{t_{\text{end}}} \text{for all} \quad t \in [0, t_{\text{end}}]. \tag{3}$$

[3]We are aware that assuming a uniform distribution can be problematic because some repair work can last a long time. Thus, during our empirical analyses t_{end} refers to the point in time until which the majority of reconstruction work has been completed, instead of focusing on the last damage repair.

Furthermore, we assume the price level at $t = 0$ to be identical for the no-catastrophe scenario and the catastrophe scenario, that is, $P_{\text{cat}}(0) = P_{\text{no-cat}}(0) =: P(0)$. On this basis the calculation of Demand Surge can be represented as follows:

$$\text{Avg. Demand Surge} = \frac{1}{t_{\text{end}}} \cdot \int_{t=0}^{t_{end}} (p_{\text{cat}}(t) - p_{\text{no-cat}}(t))\text{d}t = \frac{1}{t_{\text{end}}} \cdot \int_{t=0}^{t_{\text{end}}} \Delta p(t) dt, \quad (4)$$

where $p_{\text{cat}}(t) = P_{\text{cat}}(t)/P(0)$, $p_{\text{no-cat}}(t) = P_{\text{no-cat}}(t)/P(0)$, and $\Delta p(t) = p_{\text{cat}}(t) - p_{\text{no-cat}}(t)$.

Demand Surge From the Perspective of an Insurance Company. Within the present article we are mainly interested in the Demand Surge effect from an insurer's point of view. As already mentioned, Demand Surge effects are not limited to a particular type of catastrophe. Moreover, the effect is likewise relevant for public and private insurance companies. Thus, in addition to private insurers, our results should be of interest to public insurers, for example, for the National Flood Insurance Program (NFIP), the California Earthquake Authority (CEA), or Citizens Property Insurance Corporation (Citizens) for wind coverage in Florida. Both types of insurers have to deal with inflating claim levels due to rising reconstruction costs for insured and damaged properties. Thus, an insurer has to estimate claims payments for future catastrophes including Demand Surge effects. In the following, we assume a constant proportion $1-\rho$ of total repair costs to be attributable to materials, which virtually show no price reaction due to natural disasters. Moreover, we define claim payments$_{\text{no-cat}}(t)$ as the payout of the insurance company at time t on the basis of the no-catastrophe price level. Using this notation, the total claim payments in the catastrophe situation can be calculated as

$$\text{Total claim payments}_{\text{cat}} = \int_{t=0}^{t_{\text{end}}} \text{claim payments}_{\text{no-cat}}(t) \cdot (1 + \rho \cdot \Delta p(t))\text{d}t, \quad (5)$$

where t_{end} denotes the date of the last settled claim related to the catastrophe under observation, and $\Delta p(t)$ is the relative change of reconstruction labor costs when switching from a no-catastrophe to a catastrophe scenario as derived above.

Similar to Equation (3), we assume claim payments$_{\text{no-cat}}$ to be constant over the time period $[0, t_{\text{end}}]$. Consequently, the claim payments in the catastrophe scenario can be simplified to

$$\begin{aligned}\text{Total claim payments}_{\text{cat}} = {} & \text{claim payments}_{\text{no-cat}} \\ & \cdot \left(1 + \rho \cdot \text{Avg. Demand Surge}\right) \cdot t_{\text{end}}.\end{aligned} \quad (6)$$

Thus, an insurance company can apply Equation (6) to calculate its total claim payments including Demand Surge. When applying Equation (4) to calculate the average Demand Surge effect, it is unclear which value of t_{end} is appropriate. Against this background, we will test different values of t_{end}. McCarty and Smith (2005)

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	

analyze the 2004 hurricane season in Florida and find that, 1 year later, only 35 percent of the damaged units were repaired. Moreover, in 16 percent of the cases, reconstruction had not even been started, which might suggest that a time slot of 1 year and a corresponding value of $t_{\text{end}} = 1$ might be too short for our purposes. In addition, Belasen and Polachek (2008) state that even damages from the largest catastrophes in the past were repaired within 2 years. However, catastrophe claims are generally considered to be short tailed (Harrington, 1997; Gron, 1994), and Gron (1994) argues that from 1977 to 1986, 95 percent of homeowners' claims in the United States were paid within 3 years.[4] 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 "Measurement of Demand Surge" section a detailed description of our approach for measuring Demand Surge is given.

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. Second, we track labor price changes in the respective catastrophe areas. Finally, we subtract the change of a baseline price level to normalize the price evolution and obtain a Demand Surge measure.

[4]It should be considered that the remaining claims are possibly delayed because there is a disagreement about the payment between the insured and the insurer, and not because of limited availability of the workforces.

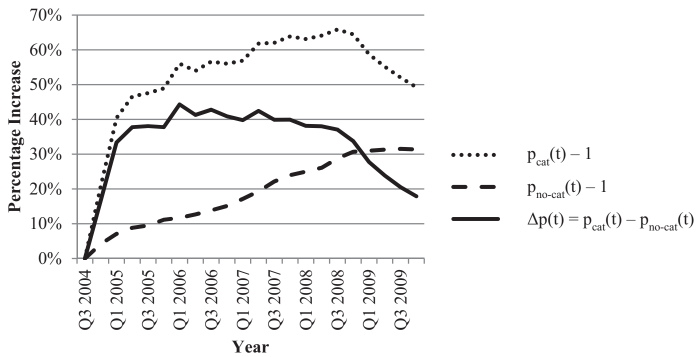
For this purpose, we use catastrophe data provided by EM-DAT.[5] EM-DAT contains all natural and man-made catastrophes since 1900 that fulfill at least one of the following criteria: (1) 10 or more people reportedly killed, (2) 100 or more people reportedly affected, (3) declaration of a state of emergency, or (4) call for international assistance (Scheuren et al., 2008). The database is composed of data filed by UN agencies, nongovernmental organizations, insurance companies, research institutes, and press agencies (Scheuren et al., 2008). All damage values therein are expressed in U.S. dollars at the time the events took place (current value) and are converted into 2005 U.S. dollars using the U.S. Consumer Price Index (CPI) for comparison. Moreover, all these values refer to direct damage (Scheuren et al., 2008). Thus, indirect damages, that is, the reduction of the total value added, are not contained (Hallegatte and Przyluski, 2010). Because small catastrophes are less likely to produce the increasing labor demand that creates Demand Surge effects, we use a cutoff value of US$100 million 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 United States and Canada and has published a retail labor index on a quarterly basis since 2002 and on a monthly basis since 2009 for each of these areas (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 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 U.S. retail labor price index. Therefore, we additionally calculate the cumulative relative change for the U.S. 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

[5]EM-DAT: The OFDA/CRED International Disaster Database-www.emdat.be-Université Catholique de Louvain-Brussels-Belgium. We are aware that this database has been criticized on some aspects. Though in the literature mentioned, drawbacks, like inconsistently added drought losses, wrongly classified wind-induced floods, or a quite lenient threshold for events to be included in EM-DAT, are not crucial for our work. Either we will not make use of this information (the catastrophe type) or will apply additional constraints for events to be included in our analyses. Against this background, we believe that EM-DAT is well suited for our purposes.

FIGURE 3
Demand Surge Measurement



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

over differing time periods of 1, 2, and 3 years and use the result as our Demand Surge measure. An example calculation is shown in Figure 3.

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 U.S. 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, for example, 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, 300, 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 450–600 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 employees 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.

In many cases, insurance payout is complemented by federal disaster relief, especially for our sample of large and extreme catastrophes. To control for this effect in our analysis we construct a dummy variable indicating whether a catastrophe affected region received federal disaster relief through a presidential (major) disaster declaration (PDD). These data were provided by the Federal Emergency Management Agency (FEMA).[6]

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 2 and 1 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 United States.

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

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.

[6]A detailed description and discussion of federal disaster relief programs in the United States is available in Sylves (2015).

TABLE 2
Variable Definitions

Variable	Definition
Damage	Direct damage of the catastrophe (in US$ billion).
$Damage^2$	Squared direct damage of the catastrophe.
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).
PDD	Dummy variable indicating whether a PDD was issued for a catastrophe (PDD = 1) or not (PDD = 0).
GDP change	Real GDP growth of the construction sector in the affected state.
Employees	Number of employees of the construction industry in the affected county/state (in millions).
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).

An overview of the set of exogenous variables used in the upcoming empirical analysis is shown in Table 2.

Descriptive Statistics

Summary statistics of our sample are presented in Tables 3–7. 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 4, 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 US$100 million, only 192 of 901 entries remain. The distribution of the damage is highly right skewed, with a mean value of US$1.597 billion, a median of US$0.250 billion, and a maximum of US$41.01 billion. 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 1-year interval for the remaining time window of up to 3 years. In more than 50 percent of all cases, at least one further catastrophe can be observed in each time slot. The number of observations for

TABLE 3
Summary Statistics—Composition of the Data Set

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

subsequent damages in the time periods [1; 1.5), [1.5; 2), and [2; 3) years after the catastrophe are smaller than for all other time windows. This is a direct result of the data availability since our data set of catastrophe events ends in 2011. Moreover, we find that the GDP change is negative in more than 75 percent of the cases, which indicates that at the time the catastrophes took place, the construction sector most likely had idle capacities. A maximum wage change of 50.98 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 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 percent of the cases. Finally, we observe that in 66 percent of the cases the affected region received federal disaster relief through a major disaster declaration.

In Table 5, the number of observations is further limited. The sample now comprises 60 catastrophe regions, with minimum sustained damages of US$500 million. As a consequence, the mean value of the damage variable of US$4.639 billion is significantly higher compared to Table 4. The same observation is true for the number of claims and the share of catastrophe regions that received a major disaster declaration. All other exogenous variables are quite similarly distributed.

In Table 6, summary statistics are presented for each measure of Demand Surge, both for large (damage $\geq$ US$100 million) and extreme catastrophes (damage $\geq$ US$500

TABLE 4
Summary Statistics—Demand Surge Drivers (Damage ≥ US$100 Million)

	Obs.	Mean	Std. Dev.	Min.	q25	q50	q75	Max.
Damage (US$ billions)	192	1.597	5.154	0.1020	0.1530	0.2496	0.6272	41.01
Subsequent damage [0; 0.5)	192	1.606	8.450	0	0	0.0639	0.3508	110.99
Subsequent damage [0.5; 1)	192	0.9770	4.985	0	0	0.0385	0.2203	57.34
Subsequent damage [1; 1.5)	180	0.8518	2.781	0	0	0.0516	0.4088	21.90
Subsequent damage [1.5; 2)	180	0.3439	1.187	0	0	0.0667	0.1697	10.29
Subsequent damage [2; 3)	156	2.166	7.134	0	0.0667	0.2089	0.7233	62.48
Previous damage [0.5; 0)	192	1.123	5.007	0	0	0.0440	0.2413	57.34
Previous damage [1; 0.5)	192	0.8415	3.957	0	0	0.0795	0.2358	32.57
Previous damage [1.5; 1)	192	0.5075	3.104	0	0	0.0595	0.1818	30.23
Previous damage [2; 1.5)	192	0.3769	2.475	0	0	0.0074	0.1007	32.57
Previous damage [3; 2)	192	1.157	4.966	0	0.0396	0.1764	0.4497	62.48
Claims (millions)	192	0.2757	0.3677	0.0028	0.0579	0.1379	0.2894	1.385
PDD	192	0.6563	0.4762	0	0	1	1	1
GDP change	192	−0.0380	0.0456	−0.2074	−0.0634	−0.0343	−0.0081	0.0630
Employees (millions)	192	0.1649	0.1582	0.0006	0.0622	0.1188	0.2119	0.8446
Wage change	192	0.0862	0.0710	0.0020	0.0513	0.0698	0.0951	0.5098
Mapping distance (km)	192	4.637	14.40	0	0	0	0	84.19

Note: The sample comprises 192 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.

million). By definition, the maximum Demand Surge effect is larger than the average Demand Surge effect for the 2-year time period. Furthermore, in every setting, the distribution is highly right skewed. For large catastrophes, the mean Demand Surge effect varies between 1.3 and 2.0 percent, whereas for extreme catastrophes, the Demand Surge effect is more pronounced, varying between 3.3 and 4.7 percent. The 95 percent quantile of the Demand Surge effect is even around 7–10 percent (21–28 percecnt) for large (for extreme) catastrophes. 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.

TABLE 5
Summary Statistics—Demand Surge Drivers (Damage ≥ US$500 Million)

	Obs.	Mean	Std. Dev.	Min.	q25	q50	q75	Max.
Damage (US$ billions)	60	4.639	8.502	0.5035	0.6788	1.698	4.576	41.01
Subsequent damage [0; 0.5)	60	2.005	4.329	0	0	0.0585	1.751	21.90
Subsequent damage [0.5; 1)	60	1.509	4.809	0	0	0.0416	0.4066	32.57
Subsequent damage [1; 1.5)	56	1.733	4.706	0	0	0.0090	0.1937	21.90
Subsequent damage [1.5; 2)	56	0.0983	0.2404	0	0	0	0.1034	1.574
Subsequent damage [2; 3)	49	0.8819	3.126	0	0.0862	0.1713	0.4981	21.42
Previous damage [0.5; 0)	60	2.106	4.780	0	0	0.1542	1.097	16.28
Previous damage [1; 0.5)	60	1.463	5.593	0	0	0.1129	0.3137	30.23
Previous damage [1.5; 1)	60	1.203	5.450	0	0.0045	0.1033	0.1775	30.23
Previous damage [2; 1.5)	60	0.1686	0.7017	0	0	0.0036	0.0692	5.140
Previous damage [3; 2)	60	0.7600	1.547	0	0	0.1694	0.4497	5.617
Claims (millions)	60	0.4837	0.4781	0.0180	0.0870	0.2720	0.6931	1.385
PDD	60	0.7500	0.4367	0	1	1	1	1
GDP change	60	−0.0275	0.0556	−0.2074	−0.0634	−0.0284	−0.0027	0.0630
Employees (millions)	60	0.1875	0.1847	0.0006	0.0668	0.1211	0.2159	0.6356
Wage change	60	0.1133	0.1085	0.0020	0.0548	0.0807	0.1012	0.5098
Mapping distance (km)	60	6.409	15.30	0	0	0	0	80.35

Note: The sample comprises 60 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.

Finally, in Table 7 the pairwise correlations between the above-described variables are presented for the full sample of observations.

EMPIRICAL ANALYSES

A Small Case Study on Demand Surge

In this section, we motivate the relevance of the Demand Surge effect by selected catastrophes. To this end, we consider 10 events known by name with the largest total damages during the time period 2002–2010. These are the Hurricanes Katrina, Ike,

TABLE 6
Summary Statistics—Demand Surge

	Obs.	Mean	Std. Dev.	Min.	q25	q50	q75	q95	Max.
Panel A: Large Catastrophes (Damage ≥ US$100 Million)									
Avg. Demand Surge: 1 year	192	0.0127	0.0418	−0.0328	−0.0051	0.0015	0.0113	0.0665	0.3146
Avg. Demand Surge: 2 years	180	0.0156	0.0529	−0.0553	−0.0086	0.0029	0.0176	0.0938	0.3650
Avg. Demand Surge: 3 years	156	0.0202	0.0622	−0.0666	−0.0083	0.0067	0.0267	0.0961	0.3791
Max. Demand Surge: 2 years	180	0.0349	0.0654	−0.0176	0.0007	0.0150	0.0422	0.1356	0.4431
Panel B: Extreme Catastrophes (Damage ≥ US$500 Million)									
Avg. Demand Surge: 1 year	60	0.0329	0.0673	−0.0133	−0.0039	0.0046	0.0404	0.2093	0.3146
Avg. Demand Surge: 2 years	56	0.0393	0.0834	−0.0193	−0.0080	0.0094	0.0444	0.2606	0.3650
Avg. Demand Surge: 3 years	49	0.0468	0.0958	−0.0307	−0.0054	0.0139	0.0485	0.2833	0.3791
Max. Demand Surge: 2 years	56	0.0629	0.1016	−0.0043	0.0022	0.0250	0.0603	0.3129	0.4431

Note: 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 US$100 million is reported; Panel B refers to observations with damage of at least US$500 million.

TABLE 7
Table of Correlations

	Dem. Surge	Damage	Claims	PDD	GDP	Empl.	Wage	Dist.
Avg. Demand Surge	1.00							
Damage	0.39	1.00						
Claims	0.25	0.47	1.00					
PDD	0.15	0.18	0.22	1.00				
GDP change	0.47	0.17	0.17	0.08	1.00			
Employees	0.06	−0.04	−0.02	−0.18	0.13	1.00		
Wage change	0.06	0.38	0.32	0.04	0.32	0.02	1.00	
Mapping distance	0.09	0.15	0.09	0.20	0.12	−0.28	0.11	1.00

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

TABLE 8
Demand Surge for Selected Catastrophes

Event	Year	Location (State)	Avg. Demand Surge	Damage (Region)	GDP Change	Wage Change
Frances	2004	Florida	0.3650	5.438	0.0536	0.0369
Ivan	2004	Florida	0.2606	11.130	0.0536	0.0526
Jeanne	2004	Florida	0.2606	8.076	0.0536	0.0526
Charley	2004	Florida	0.2476	16.203	0.0536	0.0526
Ike	2008	Texas	0.1150	4.118	−0.0078	0.0949
Katrina	2005	Louisiana	0.0920	37.794	−0.0310	0.3275
Wilma	2005	Florida	0.0628	6.881	0.0626	0.5098
Rita	2005	Mississippi	0.0473	0.128	−0.0240	0.2644
Gustav	2008	Louisiana	0.0382	5.953	0.0230	0.0681
Isabel	2003	Maryland	0.0026	0.944	−0.0127	0.0985

Note: The table reports Demand Surge for selected catastrophes and selected regions. The data set comprises the 10 catastrophes known by name with the largest total damage, and for each such catastrophe the region with the highest Demand Surge is considered. Demand Surge is computed as the average increase of the retail labor index in a 2-year period after the catastrophe, and Damage (Region) stands for the total damage of the corresponding region. The other variables are defined in Table 2.

Ivan, Charley, Rita, Wilma, Frances, Jeanne, Gustav, and Isabel. For each of these events in turn we consider the region with the largest measured average Demand Surge effect. The resulting regional events are presented in Table 8 and sorted by the extent of the Demand Surge effect.

First, it appears that four of the considered catastrophes lead to Demand Surge effects above 20 percent. In this way, it becomes clear that the Demand Surge effect can be substantial.

Second, it can be seen that not only the extent of total damages in the region is crucial for the Demand Surge effect. Rather, the largest Demand Surge effect of 36.5 percent was caused by Hurricane Frances in the region of West Palm Beach, although the total damage (US$5.438 billion) in this region was relatively low compared to other events and other regions. The reason might be that a significant amount of subsequent damages from other events occurred in the following 1.5 years, which is an indicator for the proximity catastrophe hypothesis (H2). In contrast, the largest total damage caused by Hurricane Katrina and amounting to US$37.794 billion led to a Demand Surge effect of "only" 9.2 percent in the region of New Orleans. In this context, it must be noted that the region of New Orleans was already confronted with wage changes amounting to 32.75 percent in the previous 18 months. This, in turn, is an indication of the saturation sypothesis (H6).

Third, against the background of Table 8 it is striking that Demand Surge effects tend to be lower if the economy in the construction sector is falling (negative GDP change) in comparison to the extent of Demand Surge if the economy is growing. This issue supports our growth hypothesis (H4).

All in all, this example already shows that the Demand Surge effect is highly relevant and that many factors influence the extent of Demand Surge. The detailed analysis of relationships between those factors and the Demand Surge effect is carried out in the following sections.

Demand Surge Effect for Large Catastrophes

Subsequently, we test our hypotheses from the "Hypotheses" section, which refer to the impact of catastrophe-specific variables and macroeconomic conditions on Demand Surge. According to the "Modeling of Demand Surge and Data" section, we consider catastrophe events with damages of at least US$100 million because it is unlikely that rather small events lead to a significant increase in the demand of building services and, consequently, increasing prices.[7] In order to specify the functional relationship between our Demand Surge measure and the influencing factors described in the "Demand Surge Drivers" section,

$$\text{Avg. Demand Surge} = f(\text{Dam., Alter. Dam., Claims, GDP, Empl., Wage, Controls}), \tag{7}$$

we analyze the resulting 180 observations using OLS regressions with clustered standard errors, each cluster representing one catastrophe.

We start with analyzing the impact of damage on Demand Surge before we study the influence of the other factors. According to our damage hypothesis (H1), we expect that a higher damage *ceteris paribus* leads to a higher Demand Surge effect. Though, it is unclear whether the functional relationship is linear. For example, it is indicated by Hallegatte (2008) and AIR (2009) that this dependency is concave. We study different functional forms by implementing polynomial functions Avg. Demand Surge $= \sum_{k=0}^{n} \beta_k \cdot \text{Damage}^k$ with polynomials of a degree up to $k = 4$. The results shown in Table 9 indicate that in addition to the linear term a quadratic term should be included, whereas a cubic and quartic component are not statistically significant. Thus, we focus on model (A.2). We find the linear component to be positive and the quadratic component to be negative, which confirms that Demand Surge can indeed be described as a concave function of damage.[8]

We use the quadratic function of model (A.2) as the basis for the subsequent empirical analyses. As a next step, we consider additional explanatory variables. The results are presented in Table 10.

[7]It would also be interesting to test whether the underlying economic mechanisms differ between different catastrophe types by splitting the data set into different subsamples 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.

[8]We have tested several alternative functional forms; for example, we have defined categorical damage variables to allow for arbitrary nonlinear relationships between damage and Demand Surge. We find that the polynomial function leads to a higher explanatory power, which confirms that the polynomial is well suited to reflect the dependency between damage and Demand Surge.

TABLE 9
Functional Relationship Between Damage and Demand Surge

	(A.1)	(A.2)	(A.3)	(A.4)
Damage	0.0022***	0.0092**	0.0139***	0.0166*
	(4.30)	(3.09)	(3.68)	(2.34)
Damage^2		−0.0002*	−0.0009†	−0.0015
		(−2.53)	(−1.74)	(−0.98)
Damage^3			0.0000	0.0000
			(1.31)	(0.68)
Damage^4				−0.0000
				(−0.53)
Constant	−0.0034	−0.0066**	−0.0088***	−0.0098**
	(−1.24)	(−3.26)	(−3.71)	(−2.73)
Prev. & subs. damages	Yes	Yes	Yes	Yes
Observations	180	180	180	180
Adjusted R^2	0.730	0.758	0.766	0.766

Note: 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 US$100 million. 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% levels, respectively.

In model (B.1), we test the influence of the damage caused by the catastrophe on Demand Surge. Moreover, we analyze the impact of other catastrophe events occurring in the same region less than 2 years before or after the considered event. We find that both effects are highly relevant and account for a major share of the variance of Demand Surge, which confirms the damage hypothesis (H1) and the proximity catastrophe hypothesis (H2). To be more specific, the prices of retail labor increase by approximately 3.9 (6.9) percentage points if damages due to a catastrophe rise from the mean value by one standard deviation (two standard deviations). 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 6–12 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. Our subsequent analysis confirms this view as these coefficients are no longer significant if we explicitly control for saturation effects (see model (B.4)).

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).

TABLE 10
Demand Surge for Large Catastrophes

	(B.1)	(B.2)	(B.3)	(B.4)
Damage	0.0092**	0.0081**	0.0078**	0.0083***
	(3.09)	(2.85)	(3.21)	(3.78)
Damage^2	−0.0002*	−0.0002*	−0.0002**	−0.0002**
	(−2.53)	(−2.48)	(−2.78)	(−3.09)
Subsequent damage [0; 0.5)	0.0013***	0.0013***	0.0012***	0.0014***
	(8.42)	(8.54)	(9.03)	(7.94)
Subsequent damage [0.5; 1)	0.0019***	0.0018**	0.0016**	0.0015**
	(3.60)	(3.43)	(3.34)	(3.27)
Subsequent damage [1; 1.5)	0.0090**	0.0094**	0.0091***	0.0084***
	(3.28)	(3.40)	(3.71)	(3.70)
Subsequent damage [1.5; 2)	0.0002	0.0005	0.0014*	0.0010
	(0.24)	(0.90)	(2.08)	(1.59)
Previous damage [0.5; 0)	0.0016†	0.0016†	0.0015†	0.0018*
	(1.89)	(1.90)	(1.78)	(2.29)
Previous damage [1; 0.5)	−0.0004*	−0.0004*	−0.0006*	−0.0000
	(−2.04)	(−92.45)	(−2.38)	(−0.13)
Previous damage [1.5; 1)	−0.0009	−0.0009	−0.0017**	−0.0005
	(−1.33)	(−1.54)	(−2.80)	(−0.60)
Previous damage [2; 1.5)	−0.0004	−0.0003	−0.0004	−0.0004
	(−0.62)	(−0.53)	(−0.89)	(−0.91)
Claims		0.0096†	0.0090	0.0105*
		(1.73)	(1.53)	(2.11)
PDD		0.0020	0.0002	−0.0000
		(0.52)	(0.06)	(−0.01)
GDP change			0.2366**	0.2466**
			(3.30)	(3.34)
Employees			−0.0411*	−0.0385*
			(−2.27)	(−2.24)
Wage change				−0.1072*
				(−2.10)
Mapping distance		0.0001	−0.0001	−0.0000
		(1.37)	(−0.49)	(−0.40)
Constant	−0.0066**	−0.0103**	0.0076	0.0152*
	(−3.26)	(−3.33)	(1.62)	(2.20)
Observations	180	180	180	180
Adjusted R^2	0.758	0.759	0.791	0.796

Note: 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 US$100 million. 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 percent levels, respectively.

In model (B.2), we additionally include the number of insurance claims for a catastrophe. We find that a large number of claims lead to a significantly higher Demand 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 7). However, as both variables are considered in (B.2), the number of claims does not represent the amount of damage; rather, the positive coefficient indicates that there is a higher chance that insurance claims are settled by insurers if the total number of claims is high. The underlying reason could be a less thorough investigation of claims by insurers due to limited resources. An alternative reason is that there could be high pressure on insurers to quickly settle claims as a result of politics and the media. Either way, our insurance hypothesis (H3) is confirmed.[9] In addition, we include the information whether or not a catastrophe region received federal disaster relief. At first glance, it seems to be surprising that additional federal disaster relief does not influence the Demand Surge effect. Nevertheless, it is reasonable to assume that a PDD is issued especially in those cases were the damage is high. This is indeed the case and it seems that the information about the issuance of a major disaster declaration is already captured by our damage variable. However, in a univariate setting the effect of a PDD on Demand Surge is positive as expected. Finally, we include the variable Mapping distance to consider that, in some cases, the measured price increase might underestimate the actual price increase because macroeconomic data are not available for the exact catastrophe location. This variable is not significant, which shows that the mapping seems to be appropriate.

When we integrate macroeconomic variables in model (B.3), the effects of damage and number of claims remain basically unchanged. We find that an increase of the GDP in the construction sector in the previous year significantly contributes to Demand Surge. Not only is the effect statistically significant, with $p < 1$ percent, but the economic effect is also substantial: if the GDP increases by 1 percent before a catastrophe, the resulting Demand Surge effect increases by approximately 0.24 percentage points. This finding confirms the growth hypothesis (H4), which states that Demand Surge is more pronounced if the construction sector is in a stage of growth and there is only little idle capacity. Moreover, if the number of employees in the construction sector is high, we find that the Demand Surge effect is significantly smaller, which confirms the employee hypothesis (H5). The rationale behind this result is that in such a situation, the construction industry is rather capable of dealing with the additional labor demand.

[9] In a robustness check we split the total number of claims into two variables representing the number of personal claims and the number of commercial claims. We found that all three variables are highly correlated with each other and, therefore, a split did not add additional explanatory power. Moreover, we included the average size of the claim into the model and discovered that the results were unaffected, meaning that the positive relationship between Demand Surge and the total number of claims is not driven by the average size of the claim. Further information is available upon request.

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

In summary, most effects are very stable in terms of statistical significance and absolute size. Our results suggest that all hypotheses (H1–H6) are true. Furthermore, the adjusted R^2 of up to 0.796 shows that Demand Surge can, to a large extent, be attributed to the considered effects.

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 US$100 million. 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 US$500 million. Due to the higher bound, the number of observations substantially decreases from 180 to 56. The consequence is a low number of degrees of freedom, which can easily lead to the problem of overfitting the data. To reduce this problem, we subsequently use a reduced number of explanatory variables. To be more specific, we consider only variables where we found significant effects on the larger data set.

The regression results for the subsample of extreme events are presented in Table 11. The first column is a repetition of model (B.4) to allow easier comparison of the results. Model (C.2) presents regression results for the full sample using a reduced number of explanatory variables to reduce overfitting the data. We find that the reduction of the number of variables leads to a slightly increased adjusted R^2 of 0.802, instead of 0.796. In model (C.3), we restrict the data set to the subsample of events with damages of at least US$500 million. 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. In contrast to the analysis of smaller catastrophes the damage variable and its quadratic transformation are at most weakly significant. This might be due to the small number of observations. However, if only a linear function of damage is considered, the coefficient of damage is highly statistically significant, with $p < 1$ percent. Moreover, regarding possible saturation effects we find that wage change is now highly statistically significant, with $p < 0.1$ percent. Concretely, a cost increase of building services in the preceding 18 months of 10 percent dampens the Demand Surge effect by 1.8 percentage points. Thus, for extreme catastrophes, saturation effects cause that Demand Surge to indeed be less pronounced.

In summary, for extreme catastrophes with damages of at least US$500 million, all hypotheses (H1–H6) can be confirmed. Moreover, the adjusted R^2 of 0.882 suggests

TABLE 11
Demand Surge for Extreme Catastrophes

	Damage ≥ US$100 Mio.		Damage ≥ US$500 Mio.
	(C.1)	(C.2)	(C.3)
Damage	0.0083***	0.0081***	0.0057†
	(3.78)	(4.12)	(1.98)
Damage^2	−0.0002**	−0.0002***	−0.0001
	(−3.09)	(−3.46)	(−1.70)
Subsequent damage [0; 0.5)	0.0014***	0.0014***	0.0047***
	(7.94)	(8.92)	(4.40)
Subsequent damage [0.5; 1)	0.0015**	0.0015**	0.0019*
	(3.27)	(3.35)	(2.18)
Subsequent damage [1; 1.5)	0.0084***	0.0084***	0.0065***
	(3.70)	(3.70)	(3.99)
Subsequent damage [1.5; 2)	0.0010		
	(1.59)		
Previous damage [0.5; 0)	0.0018*	0.0018*	0.0046**
	(2.29)	(2.41)	(3.03)
Previous damage [1; 0.5)	−0.0000		
	(−0.13)		
Previous damage [1.5; 1)	−0.0005		
	(−0.60)		
Previous damage [2; 1.5)	−0.0004		
	(−0.91)		
Claims	0.0105*	0.0107*	0.0241***
	(2.11)	(2.37)	(4.21)
PDD	−0.0000		
	(−0.01)		
GDP change	0.2466**	0.2399**	0.2186†
	(3.34)	(3.42)	(1.72)
Employees	−0.0385*	−0.0353*	−0.0724**
	(−2.24)	(−2.36)	(−2.83)
Wage change	−0.1072*	−0.1238***	−0.1778***
	(−2.10)	(−3.47)	(−4.20)
Mapping distance	−0.0000		
	(−0.40)		
Constant	0.0152*	0.0157*	0.0156
	(2.20)	(2.47)	(1.27)
Observations	180	180	56
Adjusted R^2	0.796	0.802	0.882

Note: 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 US$500 million. 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 percent level, respectively.

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

Robustness Checks

We performed several robustness checks, which we briefly summarize below. The detailed results can be found in the online appendix (Döhrmann, Gürtler and Hibbeln, 2015).

In the "Demand Surge Effect" sections for Large and Extreme Catastrophes, 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 percent of homeowners' claims are paid. We find that the results regarding the average Demand Surge effect during the 3-year period are very similar to those of the "Demand Surge Effect" sections for Large and Extreme Catastrophes, in terms of both statistical significance and the magnitude of the effects. The adjusted R^2 values of these models are even slightly higher compared to the analyses in the "Demand Surge Effect" sections for Large and Extreme Catastrophes.

Similarly, we examine whether the results change if we consider only 1 year after the catastrophe. We find that most of the results are similar to the previous findings. However, the adjusted R^2 is remarkably smaller compared to the previous analyses. This result suggests that it might be more appropriate to measure the economic Demand Surge effect on the basis of a longer horizon, which could also be concluded from McCarty and Smith (2005), who find that 1 year after the 2004 hurricane season, only 35 percent of the damaged buildings were repaired in full and 16 percent of the repair work had not even started.

As described in the "Theoretical Consideration of Demand Surge" section, we measure Demand Surge as the *average* price increase of building services after a catastrophe, for example, 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. We find that the results regarding the maximum Demand Surge are not substantially different from the analyses of the average Demand Surge effect in the "Demand Surge Effect" sections for Large and Extreme Catastrophes, 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.

CONCLUSIONS AND IMPLICATIONS

In this article, 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 percent 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, if the damage increased from the mean value by one (two) standard deviation(s), this leads to a price increase in retail labor of approximately 3.9 (6.9) percentage points. 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 percent before a catastrophe, we find the Demand Surge effect to rise by approximately 0.25 percentage points. 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 employees in the construction sector and Demand Surge because in such a situation the construction sector is rather capable of dealing with the additional labor demand due to the catastrophe. In addition, we observe a saturation effect, according to which a wage increase for building services before a catastrophe leads to a reduced Demand Surge effect.

Our results have important implications for insurance companies and their investors as well as issuers and investors of catastrophe-linked securities. Both public and private 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 Shelor et al., 1992; Lamb, 1995; Marlett et al., 2000; Gangopadhyay et al., 2010). 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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