Arising from the Ruins:

The Impact of Natural Disasters on Reconstruction Labor Wages

Abstract

Natural disasters represent an exogenous shock to local labor markets. Generally, the need for reconstruction creates a boom in the construction sector that can lead to wage surge for reconstruction labor. Based on 9,009 catastrophe regions in the United States we segregate the catastrophe induced wage effect from the business cycle development and find a wage surge of up to 50%. Furthermore, we find that local labor market characteristics like the GDP per worker in the local construction industry and wage differentials between the center of the catastrophe and adjacent regions have significant impact on the wage surge.

JEL classification: J23, J31, Q54, R23

1 Introduction

In recent decades the frequency and severity of natural disasters increased dramatically (Kunreuther/Michel-Kerjan, 2009). This development is accompanied by an increase in catastrophe related economic losses and is assumed to continue if effective disaster mitigation efforts are omitted (Pielke, 2005; Pielke et al., 2008). Due to the massive destruction of physical assets the basis for economic losses are generally reconstruction costs. The need for reconstruction together with the financial influx from disaster relief and insurance payouts create a reconstruction boom (Guimaraes at al., 1993). Thus, some economic sectors experience even positive effects, e.g., retail and construction. Against this background, we analyze the impact of the catastrophe induced exogenous shock to the local labor market for reconstruction services. To this end, we answer the following research questions: (i) Under which economic conditions do catastrophes lead to wage surge? (ii) What are the determinants for the magnitude of wage surge? Our results should be beneficial for various market participants. For example, governments have to deal with rising economic damages and a deep understanding of wage surge is necessary to apply appropriate price regulations; insurance companies are confronted with inflating claim levels and should consider wage surge with respect to premium calculation; building contractors could use this information for future capacity planning.

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

The remainder of this paper is structured as follows. In Section 2 we provide a review of the relevant literature and propose an approach to quantifying the wage surge. In addition, we present our hypotheses for the subsequent empirical analyses. Section 3 describes our measurement approach of wage surge and the set of explanatory variables. Afterwards we introduce our empirical strategy and the corresponding descriptive statistics. The following Section 4 contains our empirical analyses and related robustness checks. Section 5 concludes.

2 Modeling of Wage Surge and Hypotheses Development

2.1 Literature Review

Ex ante it is not clear how local labor markets react to exogenous shocks. Thus, a growing number of studies deal with exogenous demand and supply shocks and their potential consequences. The main focus of these studies is on the evolution of (un-)employment or the overall economic activity. For example, Guimaraes et al. (1993) analyze the economic consequences of Hurricane Hugo, which struck South Carolina in 1989 and was the economically most devastating storm in the history of the United States. They find that in the short run disasters may have a positive effect on the local economy and one of the sectors that benefited most was construction. In contrast, Ewing et al. (2009) conduct an impact assessment of the May 3, 1999, Oklahoma tornado on the Oklahoma City metropolitan statistical area. They observe an increase in employment growth and improved labor market stability measured in terms of volatility of the employment growth rate in the period following the tornado. In addition, Ewing/Kruse (2005) examine the impact of hurricanes during the 1990s on the unemployment rate in Wilmington (North Carolina), an area susceptible to hurricanes and tropical storms, and find an adverse impact in the short run but a positive impact in the long run. However, exogenous shocks to labor markets may not only be caused by natural disasters. Card (1990) analyzes the impact of the Mariel boatlift[1] on the Miami labor market. The massive labor force increase by 7% due to the mass immigration had no effect on wage rates. The studies most connected to our work are the ones of Belasen/Polachek (2008, 2009). Both studies investigate the effect of hurricanes in Florida on employment and earnings. Their studies are based on 19 hurricanes between 1988 and 2005 and the corresponding demand shock to the local labor market. They determine the change in average growth rate of employment and earnings of affected and neighboring counties relative to unaffected counties within the first quarter being hit by a hurricane. Their analysis is

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

provided for the economy as a whole and five industrial sectors including construction. Nevertheless, these studies lack in providing an analysis of influencing factors of wage surge and an assessment of employment and earnings development in the quarters following the catastrophe.

Finally, Olsen/Porter (2010) and Olsen/Porter (2011a) provide an overview of studies trying to estimate the total damages of catastrophe events, which should include wage surge. In this context, approaches to consider wage increases are based on simulation studies (Hallegatte et al., 2008) or focus primarily on physical variables, such as the wind speed of a hurricane, to predict cost changes of constructed baskets of repairs (Olsen/Porter, 2011b).

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

2.2 Quantifying Wage Surge

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

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

[2]

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

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

quantify the impact of a catastrophe induced wage change, we use the following definition (with P(0) := (p(1) = p(0), …, p(T) = p(0) standing for no change in the wage development):

$$\varsigma = \frac{V(P_{cat}(1,T)\,|\,\Phi)}{V(P(0)\,|\,\Phi)} - \frac{V(P_{no-cat}(1,T)\,|\,\Phi)}{V(P(0)\,|\,\Phi)}. \tag{2}$$

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

$$\varsigma = \frac{V(\Delta P(1,T)\,|\,\Phi)}{V(P(0)\,|\,\Phi)} \tag{3}$$

with

$$V(\Delta P(1,T)\,|\,\Phi) = \sum_{t=1}^{T} \frac{E(x(t)\cdot\Delta p(t)\,|\,\Phi)}{(1+r)^t} = \sum_{t=1}^{T} E\left(\frac{x(t)}{(1+r)^t}\cdot\Delta p(t)\middle|\Phi\right) \tag{4}$$

and

$$\Delta p(t) = p_{cat}(t) - p_{no-cat}(t) \tag{5}$$

as the so-called *absolute wage surge at time t*. In order to analyze the impact of the wage surge on the difference ς, it is necessary to isolate $\Delta p(t)$ from x(t) because the quantities x(t) are not representative for all concerned parties. Although the isolation of the wage surge is not immediately possible on the basis of formula (3), it is feasible to determine lower and upper bounds of ς. For this purpose, we assume that x(t) and $\Delta p(t)$ are non-negatively correlated for all t as well as $E\left(x(t)/(1+r)^t\middle|\Phi\right)$ and $E\left(\Delta p(t)\middle|\Phi\right)$ are non-negatively correlated over time.[3] Furthermore, we assume $\sum_{t=1}^{T}(x(t)/(1+r)^t)\cdot p(0)\in\Phi$ to be certain at t = 0.[4] On this basis we get:[5]

$$\frac{1}{T}\cdot\sum_{t=1}^{T} E\left(\frac{\Delta p(t)}{p(0)}\,|\,\Phi\right) \le \varsigma \le E\left(\max_{t\in\{0,\dots,T\}} \frac{\Delta p(t)}{p(0)}\,|\,\Phi\right). \tag{6}$$

If we define

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

[4] This assumption is based on the subsequent empirical analysis, where the value of total costs is an explanatory variable that is contained in our data set.

[5] The proof of the following inequalities is presented in the appendix.

$$\Delta\pi(t)=\frac{\Delta p(t)}{p(0)}=\frac{p_{cat}(t)}{p_{cat}(0)}-\frac{p_{no-cat}(t)}{p_{no-cat}(0)} \tag{7}$$

as the *(relative) wage surge at time t*, the lower bound in (6) represents the average wage surge and the upper bound stands for the maximum wage surge. In Section 3.1, we will make assumptions regarding the unknown parameters of these wage surge measures, and will describe the empirical implementation in detail.

2.3 Affected Market Participants

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

In case of natural catastrophes, **governments** have to deal with high economic damages. In this context the consideration and the comprehension of wage surge is relevant for governments to ensure adequate catastrophe precautions and appropriate price regulations in the construction sector. Such official regulatory procedures allow governments to directly manage the wage surge. Price regulations are e.g. conceivable to restrict price increases after a catastrophe, but might also lead to a longer reconstruction period because fewer workers from other regions can be attracted. However, such regulations are only reasonable if the government understands the influence of wage surge on the social welfare. Indeed, it is not immediately clear if the wage surge has a negative effect on the social welfare because higher wages imply higher supply and consequently a faster remedying of damage and a decrease in underproduction (Hallegatte et al., 2008; Hallegatte, 2008). In addition, wage surge influences catastrophe induced public spending, for example for reconstruction of public infrastructure, like schools or highways. These damages can be quite substantial. For example, Guimaraes et al. (1993) declare that 18,000 miles of highways in South Carolina were impaired by Hurricane Hugo in 1989. The impact of a resulting wage surge can be quantified with ς as defined in equation (3), where p describes an index composed of necessary building services for reconstruction of public infrastructure.

While governments focus on economic damages, **insurance companies** have to deal with inflating claim levels due to rising reconstruction costs for insured and damaged properties. Against this background, it is worthwhile to note that reconstruction labor is generally the key driver of increasing reconstruction costs as opposed to building materials (Olsen/Porter, 2011b). Thus, from an insurer's perspective, ς quantifies the effect of wage surge regarding catastrophe-induced insurance payments, and p describes an index composed of necessary building services used for reconstruction purposes. Insurance companies should consider a wage surge when calculating insurance premiums and determining the required economic capital. Similarly, regarding regulatory capital backing standards, wage surge should be considered as well because in case of tail events, like natural disasters, the consideration of wage surge may decide whether the insurance company remains solvent or not.

For **investors** of insurance companies, estimates of catastrophe related claims payments and, thus, wage surge are relevant to assess the price reactions of insurance stocks after catastrophes. This effect regarding the market value of insurance companies $V^{(\text{insurance})}$ is negative: $\frac{\partial V^{(\text{insurance})}}{\partial \varsigma} < 0$. However, investors have to consider that the market value does not only react with a decline due to claims payments, but there can be an opposing effect due to new premium income because of an increasing risk sensitivity of the population. As a consequence, the market value of insurance companies can even increase after catastrophes (Gangopadhyay et al., 2010; Lamb, 1995; Marlett et al., 2000; Shelor et al., 1992).

Issuers and investors of **catastrophe-linked securities** have to quantify the price sensitivity of these securities owing to the occurrence of natural disasters including wage surge. Particularly for Cat Bonds with indemnity trigger, the payoff directly depends on the insured losses due to the catastrophe, so that wage surge is relevant for investors of these securities. As wage surge leads to a higher likelihood that the respective layer is affected, the market value of Cat Bonds $V^{(\text{CAT})}$ is decreasing: $\frac{\partial V^{(\text{CAT})}}{\partial \varsigma} < 0$.

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

Thus, for all of these market participants, appropriately assessing wage surge should be useful.

2.4 Hypotheses

Next, we will present our hypotheses which will be tested in the empirical analyses in Section 4. If the economy in the construction sector is growing, the demand for labor can arise fast but the labor supply reacts rather slowly, so that disposable capacities vanish. This leads to a lower potential to further increase the labor force and, as a consequence, a wage increase. Based on a simulation study Hallegatte et al. (2008) show that the wage surge for the 2004 and 2005 hurricane seasons would have been much lower if the economy had been in a recession as was the case for Hurricane Andrew in 1992. In a nutshell we expect:

Growth Hypothesis (H1):

In a stage of growth for the economy, wage surge levels are higher.

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

Workload Hypothesis (H2):

A higher workload per employee in the construction sector increases the wage surge.

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

Unemployment Hypothesis (H3):

Higher unemployment rates in the catastrophe region lessen wage surge.

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

Wage Differential Hypothesis (H4):

A predominant wage differential between the catastrophe affected and surrounding regions lead to higher wage surge levels.

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

Saturation Hypothesis (H5):

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

An increasing number of insurance claims per event can lead to a less thorough investigation of claims. This might be due to two possible reasons. On the one hand, there might be pressure of local authorities to settle claims quickly. As a consequence, insurance companies might either install untrained claim adjusters or each claim adjuster has to spend less time for each assessment. Both lead to a poorer damage assessment and, finally, inflating claim levels (Thomas, 1976). On the other hand, insurance companies might be classified by insured and media according to the way they settle claims, which might have a significant impact on their future premium income (Olsen/Porter, 2010). Thus, insurance companies might settle claims that are not directly attributable to the catastrophe itself due to fraud. To provide some anecdotal evidence, RMS (2000) finds that insurance companies did not verify claims below a predefined level in the aftermath of the 1999 windstorms Lothar and Martin in France. Although a part of damaged properties might be repaired even without insurance, reconstruction is generally distributed over a longer time period and, therefore, the demand shock is less pronounced. In addition, Guimaraes et al. (1993) note that insurance payouts seem to motivate homeowners to expand and improve damaged properties, creating an additional labor demand. Against this background, we hypothesize the following:

Insurance Hypothesis (H6):

A larger number of insurance claims per event lead to higher wage surge levels.

3 Data and Empirical Strategy

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

3.1 Catastrophe Events and Wage Surge

We measure wage surge on the basis of catastrophe events in the United States that are prone to wage surge. For this purpose, we use catastrophe data provided by SHELDUS (Spatial Hazard Events and Losses Database for the United States).[6] SHELDUS contains county level data for all natural catastrophes in the United States since 1960 that caused at least one fatality and/or any economic damage.[7] The main data sources are the National Climatic Data Center (Storm Data and Unusual Weather Phenomena), the National Geophysical Data Center, and the Storm Prediction Center. All damage values therein are expressed in US 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) to allow a comparison of the values. Moreover, SHELDUS contains only direct damages, thus, indirect damages, like business interruption losses, are not contained in reported damage values. As small catastrophe events are unlikely to produce the increasing labor demand that creates wage surge, we restrict our sample to observations with damage values above the 80% quantile of the empirical damage distribution (12.16 million US-$), i.e., we only include the 20% most destructive observations in our analysis.

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

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

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

$$\frac{p_{no-cat}^{(A)}(t)-p_{no-cat}^{(A)}(0)}{p_{no-cat}^{(A)}(0)}=\frac{p_{no-cat}^{(B)}(t)-p_{no-cat}^{(B)}(0)}{p_{no-cat}^{(B)}(0)}, \tag{8}$$

where (A) denotes a catastrophe affected region and (B) a non-affected region. In this context, region (B) is similar to (A) in all respects except for the exogenous event, which is a natural catastrophe in our case. This is basically the standard assumption of the difference-in-differences approach (Ashenfelter/Card, 1985). Thus, the wage level in region (A) at time t in the no-catastrophe scenario can be calculated in the following manner:

$$p_{no-cat}^{(A)}(t)=\left(1+\frac{p_{no-cat}^{(B)}(t)-p_{no-cat}^{(B)}(0)}{p_{no-cat}^{(B)}(0)}\right)\cdot p_{no-cat}^{(A)}(0). \tag{9}$$

Against this background, we rewrite equation (7) as follows:

$$\text{wage surge }(t)=\frac{p_{cat}^{(A)}(t)}{p_{cat}^{(A)}(0)}-\frac{p_{no-cat}^{(A)}(t)}{p_{no-cat}^{(A)}(0)}=\frac{p_{cat}^{(A)}(t)}{p_{cat}^{(A)}(0)}-\frac{p_{no-cat}^{(B)}(t)}{p_{no-cat}^{(B)}(0)}, \tag{10}$$

and obtain our measures for the (relative) average and maximum wage surge:

$$\begin{aligned}\text{average wage surge} &= \frac{1}{T}\sum_{t=1}^{T}\frac{p_{cat}^{(A)}(t)-p_{no-cat}^{(A)}(t)}{p_{no-cat}^{(A)}(0)}\\ &=\frac{1}{T}\sum_{t=1}^{T}\left\{\frac{p_{cat}^{(A)}(t)}{p_{cat}^{(A)}(0)}-\frac{p_{no-cat}^{(B)}(t)}{p_{no-cat}^{(B)}(0)}\right\},\end{aligned} \tag{11}$$

$$\text{maximum wage surge} = \max_{t\in\{1,\ldots,T\}}\left\{\frac{p_{cat}^{(A)}(t)}{p_{cat}^{(A)}(0)}-\frac{p_{no-cat}^{(B)}(t)}{p_{no-cat}^{(B)}(0)}\right\}. \tag{12}$$

Unfortunately some of the parameters in equations (11) and (12) cannot directly be observed. This is the case for the point in time T of the last damage repair, and the composition of the labor price index p(t), that is not known in advance and depends on the type of catastrophe. Moreover, it is unclear which region (B) should be chosen so that the difference in differences assumption from equation (8) holds.

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

Moreover, we require a wage index p(t) representing the bulk of building services needed for reconstruction after natural catastrophes on a regional scale to measure wage surge. Xactware, a member of Verisk Analytics, Inc., offers a retail labor index for 467 economic areas in the United States and Canada. Xactware is the leading data provider for United States insuring companies and offers data on a quarterly basis from 2002 – 2008 and with a monthly frequency since 2009 (Xactware, 2012). The composition of the 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 provided in Table 1.

[Table 1]

Obviously, not every catastrophe region specified by SHELDUS is contained in Xactware. As we prefer to measure the wage surge in the center of each catastrophe region, we compute the closest Xactware localization available together with the distance between both localizations. To this end, we retrieve the geographic coordinates for each catastrophe region specified by SHELDUS and all available localizations in Xactware in WGS84 (World Geodetic System, dating from 1984 and last revised in 2004). Next, we compute for each catastrophe region in SHELDUS the distances to all available Xactware localizations (shortest distance between two points on the surface of a sphere). Finally, we retrieve the retail labor time series for the Xactware localization with the shortest calculated distance.

To segregate the relative wage increase due to a catastrophe from alternative influencing factors, we apply equation (10). Thus, we first calculate the relative change of wages in the catastrophe affected region (A), i.e., $\frac{p_{cat}^{(A)}(t)-p_{cat}^{(A)}(0)}{p_{cat}^{(A)}(0)}$ where t = 0 refers to the point in time of the occurrence of the catastrophe. As the wage evolution over time is affected by the general economic trend and cyclical variations, we have to isolate the catastrophe induced change in wage form other possible influencing factors. Therefore, we normalize the actual time series with respect to the wage evolution in the case no catastrophe had occurred (the counterfactual). Against this background, we choose the aggregated time series for the United States as a proxy for the hypothetical relative change in wage in the no-catastrophe scenario $\frac{p^{(B)}_{no-cat}(t)-p^{(B)}_{no-cat}(0)}{p^{(B)}_{no-cat}(0)}$ based on the assumption that the two abovementioned effects are both contained in the nationwide index. Of course, this choice is questionable but the task to identify an alternative county (B) being similar to the catastrophe region (A) in as many respect as possible is problematic for two reasons.[8] First, it is reasonable to assume that the counties most similar to (A) are located nearby. Unfortunately, these counties are usually affected by the same catastrophe event, too. Second, the prerequisite for a county to be non-catastrophic is that neither in the county itself nor in the greater area a catastrophe occurred in the time period from two years before to two years after the event.[9] As a consequence, according to our dataset nearly all regions are catastrophe affected. Thus, the choice of the nationwide index seems plausible, as the effects of single catastrophes on the aggregate nationwide index can be regarded as negligible. Afterwards, we calculate the difference between both relative changes and assume that the gap between both is completely attributable to wage surge. Finally, we calculate the average and maximum wage surge for time periods of T = 1, 2, and 3 years based on equations (11) and (12). An exemplary calculation of this procedure with respect to the landfall of Hurricane Frances in West Palm Beach (Florida) in Q3 2004 is shown in Figure 1.

[Figure 1]

3.2 *Wage Surge Drivers*

Direct damage values are reported by SHELDUS on a county level. Because different counties specified by SHELDUS as catastrophe regions regarding the same event may be mapped to the identical Xactware localization and all of our economic variables are related to

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

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

this Xactware localization, we apply a reassessment algorithm that combines these observations into one single new observation. The new direct damage value is the sum of all combined original damage values. For our upcoming empirical analyses we define our direct damage variable as the sum of the damage in the catastrophe localization specified by Xactware and direct damages in a given radius of 300 km around this localization. Regarding the choice of the radius we also tested alternative radii of 150, 450, and 600 km. As a selection criterion we used the adjusted R^2 of models containing the direct damage variable and direct damages of previous and subsequent catastrophes within each potential radius together with year fixed effects.[10] To control for the effect of direct damages on wage surge, we included our damage variable and its corresponding quadratic.[11]

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

As an important influencing factor on wage surge we include the state of the economy in the construction sector and obtain a variable to test the Growth Hypothesis (H1). To this end, we use data from the Bureau of Economic Analysis (BEA), which provides yearly data regarding the real GDP in the construction sector on the metropolitan statistical area (MSA) and state level. Obviously, the catastrophe affects the GDP at least in the year the catastrophe takes place. Thus, we compute the relative change in GDP between two and one year before the catastrophe, and use MSA data for localizations at the MSA level whereas using state data for counties in our sample.[12]

To test our Workload Hypothesis (H2) we calculate the real GDP per worker in the construction sector. Again, information regarding the real GDP in the construction sector stem from the BEA, whereas the number of workers in the construction sector is provided by the Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages (QCEW) program. All figures are either on the MSA or state level and refer to the realized ratio in the

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[10] The results of this preliminary cross sectional regression analysis are available upon request.

[11] We also tested a linear specification and a version where we used a categorical damage variable with 10 different categories to describe the variation in our wage surge measure. Comparing these three models the combined linear and quadratic term model was the best with respect to the obtained adjusted R^2. As further control variables we only included year fixed effects and damage values for alternative catastrophes.

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

preceding year. The rationale behind this construction is that figures for the current year might be distorted by the catastrophe.

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

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

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

Information regarding insurance claims is provided by Property Claims Services (PCS). PCS is a unit of Insurance Services Office (ISO) and the only data provider for insured catastrophic losses in the United States. PCS provides information on the number of claims in different lines of business including personal and commercial. Moreover, their estimates are accepted as triggers in Cat Bonds. All of these data are available on the state level and are assigned to each observation in our sample which is reported either on the MSA or county level. To test our Insurance Hypothesis (H6) we calculate the sum of the number of claims in commercial and personal lines of business.

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

An overview together with a brief description of our explanatory variables is provided in Table 2.

[Table 2]

3.3 Empirical Strategy

The aim of the upcoming empirical analyses in Section 4 is twofold. First, we want to determine influencing factors of the occurrence of a substantial wage surge. Second, given such an observation we want to quantify the magnitude of the effect. In order to estimate the occurrence of substantial wage surge, we first have to provide a formal definition what we mean by substantial. Next, we will describe our approach to categorize each observation in our sample. To this end, we calculate for each localization specified by Xactware (county or MSA) and each point in time the average and maximum wage surge for different time periods of T = 1, 2, and 3 years irrespective of whether a catastrophe occurred in any combination of space and time. On the one hand, the subset of observations with high wage increases is of particular importance. On the other hand, it is reasonable to assume that observations with small wage increases are disproportionally affected by noise resulting from measuring problems. These might be a direct result of the fact that the nationwide wage evolution is not a perfect proxy for the unobservable wage evolution in the no-catastrophe scenario as opposed to the assumption in the implementation of the difference in differences approach. Against this background, we will only further investigate observation with high wage increases. The necessary threshold to classify an observation to have a substantial wage surge is based upon the empirical distribution of our wage surge variables. Thus, in a second step, we calculate the mean μ and standard deviation σ for each empirical distribution of a wage surge measure. To this end, we include combinations of space and time that do not correspond to a catastrophe. In this case, a wage surge different from zero is due to measurement problems. We explicitly do not focus on non-catastrophic observations only because it is not clear which observations are completely non-catastrophic. As we assume that alternative catastrophes within a radius of 300 km in a time period from up to 3 years before to 3 years after the event affect the wage evolution of the county or MSA under observation, almost all observations are at least indirectly affected by a catastrophe. The respective statistical parameters can be found in Table 3.

[Table 3]

Finally, we define a wage surge of a given catastrophe region to be substantial if the respective wage surge is larger than $\mu + \sigma$:[13]

$$1_{\text{wage surge}} = \begin{cases} 1, & \text{if wage surge } \geq \mu + \sigma; \\ 0, & \text{otherwise.} \end{cases} \tag{13}$$

The first task is conducted with the help of a discrete choice model. To this end, we specify the probability of observing a substantial wage surge, given the set of covariates X described in Section 3.2, as our dependent variable: $P(1_{\text{wage surge}} = 1|X = x) = g(x'\beta)$. As a link function $g(\cdot)$ we use the logistic function $g(z) = e^z/(1+e^z)$, i.e., we subsequently conduct a logit analysis. In this case, the estimation of the coefficient vector β is straightforward with maximum likelihood estimation. Based on the subset of observations with substantial wage surge, we additionally conduct a cross sectional regression analysis with robust standard errors to investigate the influence of the set of covariates X on the magnitude of wage surge. Thus, we use a specification of the form: wage surge = f(X).

3.4 Descriptive Statistics

Descriptive statistics of our dataset are provided in Tables 4 to 7. To provide an overview of the full sample which spans the time period 2002–2010, we report the distribution of catastrophes over years along with the type of catastrophe in Table 4. The number of observations is quite uniformly distributed across years except for the year 2008. While losses in this year were non extraordinary large, the number of events was the highest since 1998 (Insurance Information Institute, 2009). In addition, Panel B shows the types of disaster which are in 77% of the cases storms and in 21% floods. Against this background, we will additionally split the sample in the upcoming empirical analyses into subsamples of storm and non-storm events.

In Table 5 summary statistics are presented for each of our measures for wage surge. Panel A refers to the full sample of observations used in the upcoming logit analysis in Section 4.1. The mean wage surge varies between 0.4% and 0.8% and is highly right skewed. By

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

definition, the maximum wage surge is larger than the corresponding average wage surge. In Panel B the sample is restricted to observations with a substantial wage surge as defined in Section 3.3. This subsample is used in the following cross sectional regression analysis. Obviously the average wage surge is more pronounced in this case with values ranging from 6.0% to 10.4%. Again, the distribution is right skewed. Finally, the mean values for the maximum wage surge increase from Panel A to B and now vary from 9.2% to 18.0%.

Table 6 presents summary statistics for our set of explanatory variables. We included only observations with a damage value larger than the 80% quantile of the empirical damage distribution for the years 2002-2010. Thus, 9,009 out of originally 45,049 observations remain in the full sample. The distribution of our damage variable is right skewed with a mean value of 0.46 billion US-$, a median of 0.05 billion US-$, and a maximum of 71.51 billion US-$. Regarding subsequent and previous damages resulting from alternative catastrophes, we calculate direct damage values for time intervals of half a year up to 2 years before or after the considered event and choose a time interval of 1 year for the remaining time horizon of 2 to 3 years before or after the event. The number of observations of subsequent damages in the time interval 2 to 3 years after a catastrophe differs from the rest as we excluded all observations in the year 2010 in this case. The reason is that our database of catastrophe events in the United States ends in 2012, and, therefore, we do not have the data available to calculate the subsequent damages for catastrophes occurring in 2010. Furthermore, nearly all observations sustain another catastrophe in a radius of 300 km during each of these time periods. Moreover, the variable GDP change is negative in more than 75% of the cases. This indicates that in most cases the economy has been in a recession and the construction sector possibly had idle capacities. A maximum wage change of 52.70% corresponds to the landfall of Hurricane Wilma in Melbourne (Florida) in October 2005. In this case, the current wage level is probably already highly driven by wage surge, as in the preceding 18 months Hurricanes Charley, Frances, and Jeanne occurred in Florida. The number of claims is only reported for storm events. This is due to the fact that damages due to floods in the United States are mainly insured by the National Flood Insurance Program (NFIP) and not by private companies. As a result insured damages to properties resulting from floods are not covered by PCS. Regarding the mapping distance, which measures the distance between the catastrophe localization and the localization of the assigned economic variables, we discover a mean value of 45.91 km. Thus, in most of the cases we can find a good matching. The maximum value of 629 km refers to a catastrophe event in Alaska. If we would exclude all catastrophe events in Alaska, the maximum would substantially decrease to 267 km.

Finally, Table 7 presents pairwise correlations between the economic variables and the average wage surge for the 2 year time period.[14] Based on this univariate analysis, it can be noted that the correlation coefficients between almost all economic explanatory variables and the average wage surge have the expected sign based on the hypotheses in Section 2.4. The only exception in this regard is the positive correlation between wage change and the average wage surge that contradicts our *Saturation Hypotheses (H5)*. Nevertheless, the coefficient is close to zero in this case and the wrong algebraic sign might result from an omitted variable bias. Thus, in the next section we will analyze, whether or not these findings do still hold in a multivariate setting.

[Table 4]
[Table 5]
[Table 6]
[Table 7]

4 Results

4.1 Under which Conditions do Catastrophes Lead to Wage Surge?

Next, we will analyze which catastrophe specific and macroeconomic factors influence the occurrence of a substantial wage surge, i.e., we will test the hypotheses from Section 2.4. As already described in Section 3.3 a wage surge is defined to be substantial if its value lies at least one standard deviation above the mean wage surge of its empirical distribution. To exclude conceivably non catastrophic events, we only incorporated the 20% most devastating catastrophes in terms of direct damage during the time period 2002-2010.

Table 8a provides a group comparison of observations with substantial versus non-substantial wage surge. Results are provided for a group classification based on the average and maximum wage surge in a period of two years after the catastrophe. We report mean values for our set of explanatory variables for both groups together with the pairwise mean difference. Based on these results, we can confirm all of the hypotheses from Section 2.4 except the *Saturation Hypothesis (H5)*. All pairwise differences have the expected sign and are highly statistically significant. An exception in this respect is only the variable wage change, which measures wage increases in a period of 18 months prior to the catastrophe. In

[14] The pairwise correlations regarding the maximum wage surge for the 2 year time period are comparable to the average wage surge. Details are available upon request.

both settings the group of observations with substantial wage surge exhibit a higher preceding wage increase which contradicts our *Saturation Hypothesis (H5).*

[Table 8a]

In addition, Table 8b provides results for the logit analysis based on the remaining 7,688 observations. Results for the average wage surge in a 2-year period after the catastrophe are provided in columns (A.1) to (A.3) and results for the corresponding maximum can be found in the following three columns (A.4) to (A.6). In addition, we investigate three different samples for each measure of wage surge: the full sample of observations (columns (A.1) and (A.4)), the subset of storm events (columns (A.2) and (A.5)), and the subsample of non-storm events only (columns (A.3) and (A.6)).

[Table 8b]

First, we will focus on the results for the average wage surge. Regarding the influence of damage we observe a statistically significant positive effect. This effect is particularly high for the subsample of non-storm events. If the damage increases by one standard deviation from $\mu - 0.5 \cdot \sigma$ to $\mu + 0.5 \cdot \sigma$, the probability of observing a substantial wage surge increases by 13.5%.[15]

Both of our variables describing the state of the economy in the construction sector, GDP change and GDP per worker, are significant on the full sample and the subsample of storm events. Thus, both, a growing economy and a predominant higher workload in the construction sector have the hypothesized impact on the occurrence of substantial wage surge. However, for non-storm events the coefficients have the expected sign but the results are not significant. Therefore, we can confirm our *Growth Hypothesis (H1)* and *Workload Hypothesis (H2)* for the full sample and the subsample of storm events.

In contrast, an increase of the unemployment rate by one standard deviation dampens the probability of substantial wage increases by 1% - 3% depending on the sample. Moreover, this effect is statistically significant which confirms our *Unemployment Hypothesis (H3).*

To test our *Wage Differential Hypothesis (H4)* we include the variable wage differential. We find that the coefficient is indeed positive and highly statistically significant. If wage

[15] In the following, the impact of changing the explanatory variable by one standard deviation always refers to an increase of the considered variable from $\mu - 0.5 \cdot \sigma$ to $\mu + 0.5 \cdot \sigma$, and the other variables are at their means.

differentials increase by one standard deviation the probability of a substantial wage surge rises by around 3%. To measure saturation effects we include the variable wage change, which measures the relative wage increase in the preceding period of 18 months prior to the catastrophe. This effect is negative for all samples. Nonetheless, the effect is only significant for the subsample of non-storm events. Thus, we find only weak evidence for the *Saturation Hypothesis (H5)* based on the logit analysis.

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

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

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

4.2 What are the Determinants for the Magnitude of Wage Surge?

Next, we analyze the influence of our set of explanatory variables on the magnitude of wage surge. For this purpose, we consider the subset of observations with a substantial wage surge. Thus, we exclude all observations with wage surge being less than $\mu + \sigma$. We analyze the impact of influencing factors using OLS regressions with robust standard errors. Again, in Table 9, columns (B.1) to (B.3) refer to the average wage surge in a time horizon of two years after the catastrophe, whereas columns (B.4) to (B.6) refer to the maximum wage surge. Moreover, we analyze three different samples: the full sample (columns (B.1) and (B.4)), the subset of storm observations (columns (B.2) and (B.5)), and the subset of non-storm observations only (columns (B.3) and (B.6)).

[Table 9]

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

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

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

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

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

In Section 2.4 we argued that there could be saturation effects due to wage increases in the preceding period of 18 months. We find that this effect is only significant for the full sample with respect to the average wage surge, which is in line with our *Saturation Hypothesis (H5)*. However, for all other settings the effect is insignificant.

The effect of the number of insurance claims on wage surge is insignificant in all settings, so we cannot confirm the *Insurance Hypothesis (H6)*.

If we analyze the maximum wage surge presented in columns (B.4) to (B.6), we find that most of the effects are quite similar with respect to the significance of the regression coefficients of our explanatory variables. Though, in most of the cases the absolute size of the coefficients is larger for the maximum wage surge. Nevertheless, there are some differences. The effect of preceding wage changes is insignificant in every setting for the maximum wage surge. In line with this finding, a higher unemployment rate has no significant restraining effect on wage surge too, irrespective of the considered sample. In contrast, the effect of predominant wage differentials is more pronounced. A ten percentage point increase in our wage differential measure leads to a 1.03 to 1.07 percentage points increase in wage surge.

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

4.3 Robustness Checks

In Sections (4.1) and (4.2) we analyzed the effect of catastrophe specific and macroeconomic variables on the average and maximum wage surge in the following time period of two years. As already stated in Section 3.1, we believe that a time period of two years is reasonable, but as a robustness check we will also provide analyses for the average and maximum wage surge in time periods of one and three years after a catastrophe for the full sample of observations. For example, Gron (1994) finds that approximately 95% of homeowners' claims in the United States are paid within 3 years. Thus, at least all insured damages to properties should be repaired within a time horizon of 3 years. Against this background, we assume that a time horizon of 3 years is a good choice for an upper bound. In this case, one additional year is required to calculate our endogenous variable. As a consequence the number of observations is reduced to 6,810 instead of 7,688 for the 2-year period in the logit analysis. For the same reason, the sample increases to 8,788 when analyzing the 1-year wage surge. Table 10 provides an overview of the results regarding the average wage surge.

[Table 10]

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

Regarding the analysis of the magnitude of the average wage surge most effects are similar to the results for the average wage surge for the full sample reported in Table 9. One minor difference is that the influence of a rising economy and prevalent wage differentials in the construction sector are highly significantly positive in all settings, but the economic effect is more pronounced for the 3-year time period. Furthermore, the effect of preceding wage increases on the average wage surge is insignificant in the 3-year time period. Finally, the adjusted R^2 is increasing with the time horizon used to measure the average wage surge. The lowest value can be observed for the 1 year setting (48%) and the highest for the 3 year setting (67%).

In line with the procedure for the average wage surge, we present the same analyses for the maximum wage surge in time periods of one and three years after the catastrophes in Table 11.

[Table 11]

Regarding the results of the logit analyses, which are presented in columns (D.1) and (D.2), it can be stated that the findings for the maximum wage surge are similar to the ones for the average wage surge. Again, the effect of damage on wage surge is the highest for the 1-year time period. In contrast, the effect of prevalent wage differentials on the probability of observing a substantial wage surge is more pronounced for the 3-year time period. Lastly, the adjusted McFadden R^2 increases from 20.3% (T = 1) to 21.2% (T = 2) and finally reaches a value of 28.1% (T = 3).

The results regarding the influence of catastrophe specific and macroeconomic factors on the magnitude of the maximum wage surge are provided in columns (D.3) and (D.4). In comparison with the full model for the 2-year time period in Table 9, most results are comparable. The relationship between damage and the maximum wage surge is concave for all considered time horizons. Furthermore, the effect of the unemployment rate is insignificant in all settings. In line with the findings for the average wage surge the positive effect of prevalent wage differentials is increasing with the time horizon T used for the calculation of the maximum wage surge. The effect of a percentage point increase in the measured wage differential increases from 0.07 percentage points (T = 1) to 0.10 percentage points (T = 2) and finally reaches a value of 0.20 percentage points (T = 3). The opposite effect can be observed regarding the prevailing workload in the construction sector. Last but not least, the effect of wage increases in the preceding period of 18 months prior to the catastrophe is only significantly negative for the 1-year time horizon.

5 Conclusions and Implications

In this paper we provide an analysis of increasing wages of skilled reconstruction labor in the aftermath of natural catastrophes in the United States. Our contribution is twofold. First, we identify catastrophe specific and macroeconomic conditions that lead to a substantial wage surge. Second, given this subset of observations with a substantial wage surge we quantify its magnitude and determinants. We believe that our results are beneficial for several market participants, including governments, insurance companies and their investors, building contractors, as well as issuers and investors of catastrophe linked securities, like, e.g., Cat Bonds. According to the results of our empirical analyses, almost all factors influencing the occurrence of a substantial wage surge are also able to quantify the magnitude. The results for the hypotheses analyzed in this work are summarized in Table 12. To be more specific, we identify a positive relationship between the GDP of the construction sector and wage surge.

An increase of one percentage point in GDP prior to the catastrophe leads to a 0.12 percentage point increase in wage surge. In line with this finding, a higher workload in the construction sector pushes wages upward, too. A restraining effect can be observed for regions with higher unemployment rates. Thus, it seems that at least part of the additional labor demand can be satisfied by unemployed. In contrast, prevalent regional wage differentials have the opposite effect. In concrete terms, a ten percentage point more pronounced wage differential leads to a 0.7 percentage point increase in the average wage surge. Moreover, preceding wage increases in a time period of 18 months prior to the catastrophe event dampen further wage increases due to saturation effects. In contrast, a higher number of insurance claims per event only influences the probability of occurrence of a substantial wage surge but is not able to describe its magnitude. All of our results are confirmed by several robustness checks. Moreover, the adjusted R^2 with values up to 71% shows that our considered economic mechanisms are able to explain the variation in wage surge to large extent. To sum up, our models are able to identify and quantify significant wage increases in the aftermath of natural disasters.

[Table 12]

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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	

Table 2: Description of explanatory variables

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

Table 3: Distribution of wage surge

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

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

Table 4: Summary statistics - composition of the data set

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

Table 5: Summary statistics – Wage surge

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

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

Table 6: Summary statistics – Wage surge drivers

The sample comprises 9,009 catastrophe events with a damage value above the corresponding 80%-quantile of the empirical damage distribution. 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)	9,009	0.4584	3.514	0.0122	0.0222	0.0525	0.1438	71.51
Subsequent damage (0; 0.5]	9,009	0.6170	4.679	0	0.0262	0.0737	0.2434	76.24
Subsequent damage (0.5; 1]	9,009	0.5792	4.537	0	0.0224	0.0715	0.2195	76.31
Subsequent damage (1; 1.5]	9,009	0.4301	1.324	0	0.0262	0.0783	0.2729	15.63
Subsequent damage (1.5; 2]	9,009	0.3761	2.437	0	0.0195	0.0591	0.1911	74.67
Subsequent damage (2; 3]	8,053	1.727	8.395	0	0.0976	0.2797	0.6842	76.39
Previous damage [0.5; 0)	9,009	0.4837	3.469	0	0.0208	0.0637	0.1964	73.23
Previous damage [1; 0.5)	9,009	0.3973	2.474	0	0.0234	0.0689	0.2363	73.21
Previous damage [1.5; 1)	9,009	0.5908	4.212	0	0.0228	0.0741	0.2064	76.31
Previous damage [2; 1.5)	9,009	0.2165	1.168	0	0.0210	0.0582	0.1736	72.09
Previous damage [3; 2)	9,009	0.7768	2.989	0.0001	0.0868	0.1911	0.4724	72.92
GDP change (in %)	9,009	-4.372	6.902	-40.92	-8.108	-4.035	-0.6329	30.82
GDP per worker (thousands)	9,002	76.12	14.44	45.26	64.81	74.57	84.85	140.9
Unemployment rate (in %)	9,009	5.978	2.201	1.6	4.5	5.5	6.9	24.9
Wage differential (in %)	8,809	0.6984	6.516	-27.94	-3.939	0.6986	5.014	28.75
Wage change (in %)	8,992	7.795	5.933	-6.518	4.028	6.755	10.36	52.70
Number of claims (thousands)	6,973	1.813	11.55	0	0	0.0060	0.2820	372.6
Mapping distance (km)	9,009	45.91	29.45	0	27.99	42.35	59.60	629.0

Table 7: Table of Correlations

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

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

Table 8a: Group comparison of substantial and non-substantial wage surge

The table reports the mean differences between the groups of substantial and non-substantial wage surge for several explanatory variables. In any setting the wage surge is calculated in a period of two years 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.

	Average Wage Surge			Maximum Wage Surge		
	Mean (substantial)	Mean (non-substantial)	Pairwise difference	Mean (substantial)	Mean (non-substantial)	Pairwise difference
Damage	2.057	0.2700	1.787***	1.724	0.3242	1.400***
			(14.41)			(11.13)
GDP change	-1.342	-3.570	2.228***	-1.803	-3.496	1.693***
			(11.13)			(8.36)
GDP per worker	81.03	76.40	4.626***	82.16	76.25	5.916***
			(9.64)			(12.29)
Unemployment rate	5.202	5.697	-0.4949***	5.150	5.703	-0.553***
			(-7.91)			(-8.77)
Wage differential	2.495	0.4661	2.029***	2.278	0.5067	1.771***
			(9.41)			(8.09)
Wage change	9.122	8.591	0.5309**	8.940	8.620	0.321†
			(2.80)			(1.68)
Number of claims	6.538	1.239	5.299***	5.453	1.397	4.056***
			(11.51)			(8.74)
Mapping distance	44.06	46.12	-2.059*	43.38	46.22	-2.832**
			(-2.12)			(-2.89)

Table 8b: Wage surge for different samples – logit model

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

	Average Wage Surge (2 years)			Maximum Wage Surge (2 years)		
	Full	Storm	Non-Storm	Full	Storm	Non-Storm
	(A.1)	(A.2)	(A.3)	(A.4)	(A.5)	(A.6)
Damage	0.0657***	0.0402***	0.3027***	0.0464***	0.0319***	0.0544**
	(4.81)	(3.62)	(3.96)	(6.02)	(3.42)	(3.16)
GDP change	0.0253***	0.0313***	0.0118	0.0114†	0.0142†	0.0067
	(3.76)	(3.85)	(0.97)	(1.67)	(1.70)	(0.56)
GDP per worker	0.0172***	0.0209***	0.0015	0.0157***	0.0172***	0.0073
	(5.42)	(5.62)	(0.25)	(4.77)	(4.43)	(1.11)
Unemployment rate	-0.1053***	-0.0922**	-0.1347*	-0.1638***	-0.1457***	-0.2176***
	(-3.79)	(-2.85)	(-2.56)	(-5.48)	(-4.18)	(-3.86)
Wage differential	0.0666***	0.0710***	0.0498***	0.0626***	0.0608***	0.0626***
	(10.26)	(9.18)	(3.92)	(9.17)	(7.47)	(4.68)
Wage change	-0.0114	-0.0141	-0.0501*	-0.0097	-0.0169	-0.0111
	(-1.38)	(-1.44)	(-2.37)	(-1.08)	(-1.62)	(-0.50)
Number of claims		0.0166***			0.0105**	
		(3.74)			(2.93)	
Mapping distance	-0.0001	0.0028†	-0.0081*	-0.0019	-0.0006	-0.0046
	(-0.07)	(1.66)	(-2.43)	(-1.19)	(-0.32)	(-1.36)
Constant	-3.1916***	-3.8585***	-0.4073	-2.4990***	-2.7276***	-1.2979
	(-8.53)	(-8.79)	(-0.55)	(-6.50)	(-6.19)	(-1.60)
Prev. and subs. damages	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	7,688	5,974	1,714	7,688	5,974	1,482
Adj. McFadden R^2	0.188	0.192	0.207	0.212	0.212	0.173

Table 9: Wage surge for different samples – OLS model

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

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

Table 10: Average wage surge for alternative specifications

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

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

Table 11: Maximum wage surge for alternative specifications

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

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

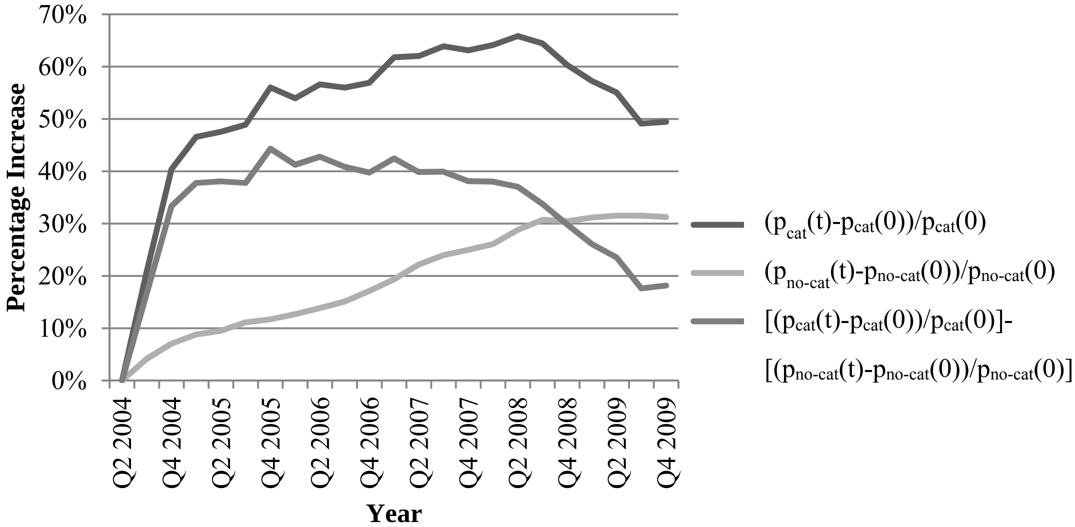
Table 12: Summary of results

This table summarizes the hypotheses and results regarding the positive or negative dependence of wage surge.

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

Figure 1: Wage Surge Measurement

In this figure our measurement of wage surge is depicted. We compute the percentage increase of the retail labor price index in West Palm Beach (p_{cat}) and the entire US ($p_{no\text{-}cat}$) starting directly before the landfall of Hurricane Frances in West Palm Beach in Q3 2004. In a second step, we calculate the difference between both time series of percentage increases according to Equation (10). Finally, we calculate the average/maximum value over differing time periods of 1, 2, and 3 years.



Appendix: Proof of inequality (6)

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

$$\frac{E\left(x(t)\cdot\Delta p(t)\middle|\Phi\right)}{(1+r)^t} \geq \frac{E\left(x(t)\middle|\Phi\right)}{(1+r)^t}\cdot E\left(\Delta p(t)\middle|\Phi\right) \text{ for all } t \in \{1, \ldots, T\}. \tag{14}$$

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

$$\frac{1}{T}\cdot\sum_{t=1}^{T}E\left(\frac{x(t)}{(1+r)^t}\middle|\Phi\right)\cdot E\left(\Delta p(t)\middle|\Phi\right) \geq \frac{1}{T}\cdot\sum_{t=1}^{T}E\left(\frac{x(t)}{(1+r)^t}\middle|\Phi\right)\cdot\frac{1}{T}\cdot\sum_{t=1}^{T}E\left(\Delta p(t)\middle|\Phi\right). \tag{15}$$

On the basis of (4) the inequalities (14) and (15) imply that a lower bound can be determined as follows:

$$\begin{aligned} &V(\Delta P(1,T)\,|\,\Phi) \geq \sum_{t=1}^{T}E\left(\frac{x(t)}{(1+r)^t}\middle|\Phi\right)\cdot\frac{1}{T}\cdot\sum_{t=1}^{T}E\left(\Delta p(t)\middle|\Phi\right) \\ \Leftrightarrow\ &\frac{V(\Delta P(1,T)\,|\,\Phi)}{V(P(0)\,|\,\Phi)} \geq \frac{\frac{1}{T}\cdot\sum_{t=1}^{T}E\left(\Delta p(t)\middle|\Phi\right)}{p(0)}. \end{aligned} \tag{16}$$

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

$$\begin{aligned} V(\Delta P(1,T)\,|\,\Phi) &= \sum_{t=1}^{T}E\left(\frac{x(t)}{(1+r)^t}\cdot\Delta p(t)\middle|\Phi\right) \leq \sum_{t=1}^{T}E\left(\frac{x(t)}{(1+r)^t}\cdot\Delta p_{max}\middle|\Phi\right) \\ &= E\left(\sum_{t=1}^{T}\frac{x(t)\cdot p(0)}{(1+r)^t}\cdot\frac{\Delta p_{max}}{p(0)}\middle|\Phi\right) = \sum_{t=1}^{T}\frac{x(t)\cdot p(0)}{(1+r)^t}\cdot\frac{E\left(\Delta p_{max}\middle|\Phi\right)}{p(0)}. \end{aligned} \tag{17}$$

The latter equality results from the assumption $\sum_{t=1}^{T}x(t)\cdot p(0)/(1+r)^t \in \Phi$. Because against this background we also get $V(P(0)\,|\,\Phi) = \sum_{t=1}^{T}x(t)\cdot p(0)/(1+r)^t$, (17) is equivalent to

$$\frac{V(\Delta P(1,T)\,|\,\Phi)}{V(P(0)\,|\,\Phi)} \leq \frac{E\left(\Delta p_{max}\middle|\Phi\right)}{p(0)}, \tag{18}$$

which provides an upper bound and completes the proof.