Economic Shocks and Labour Market Flexibility

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Abstract

We test how labour markets adjust to large, but temporary, economic shocks in a context in which such shocks are common. Using an individual-level panel, from 1,140 Philippine municipalities over 26 quarters, we find that workers in areas affected by strong typhoons experience reductions in hours worked and hourly wages, without evidence of layoffs. The results are strongest for formal, wage-paying jobs. We argue that those results are best explained by implicit contracts where workers and firms share risks. We provide extensive qualitative data suggesting that employment contracts in the Philippines allow for such flexibility.

JEL codes: J22, J30, J41, Q54

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I Introduction

How do labour markets adjust to large economic shocks? A large literature has looked at the response of wages and employment to labour productivity shocks. Nominal wage rigidities have been shown to prevent labour markets from clearing after economic shocks, leading to excess unemployment (Bewley, 1999; Kaur, 2014). These rigidities can have negative welfare consequences, especially in developing countries, where social safety nets are less common. The extent to which labour markets are able to adjust to shocks - particularly large environmental shocks - can thus determine their overall impact (Dell et al., 2014; Hsiang and Jina, 2014).

Testing for the existence of downward nominal wage rigidities, or lack thereof, is challenging. Few studies have been able to account for issues related to aggregation bias due to changes in the composition of job types or the workforce that might accompany shocks, including changes due to migration and labour supply (Keane et al., 1988; Bils, 1985). Such evidence requires not only plausibly exogenous labour demand shocks (for which there is sufficient variation over time and space), but also shocks large enough to affect the marginal revenue product of non-agricultural labour. If wage adjustments are short-lived, high-frequency data may be required to track the effects of shocks over time. Evidence from non-agricultural contexts in developing countries is particularly limited.

We overcome these challenges by leveraging a unique series of nationally representative labour force surveys in the Philippines, which cover more than 3.4 million individuals in 1,140 municipalities over 26 quarters between 2003 and 2009. Further we use a individual panel dataset formed of a substantial subset of individuals who were interviewed more than once. We combine this data with geo-referenced data on the path and strength of typhoons over the same period. Controlling for time and municipality fixed effects, we utilize the arguably exogenous nature of typhoon occurrence to estimate how labour markets adjust to large, but temporary, labour demand shocks.

First, we use the municipal-level data to show that large storms act as short-lived labour demand shocks. We find that large storms do not affect employment rates, but lead to a 7 percent reduction in per capita wage income. This impact on incomes is driven by a reduction in both the average number of hours worked per worker and in the average hourly wage. Those impacts are short-lived, as the estimated effects are no longer significant after one-quarter. There are many channels through which storms can have an impact on the marginal revenue product of labour, including the destruction of capital and infrastructure, or a decline in prices due to disruptions to trade or local consumer demand. We cannot distinguish between these channels: indeed a large literature on natural disasters suggests that many of these factors could be at play. Instead, we look at how labour market conditions are affected in the aggregate by such shocks while accounting for possible changes in labour supply.

Second, we use individual-level data to establish that nominal wages exhibit downward flexibility when storms hit. We find large and significant negative impacts on average weekly wages while confirming that there is no effect on employment rates.[1] The impact on weekly wages is driven by reductions in both the number of days worked and the number of hours worked per day. The adjustment in hours per worker is not due to some workers taking zero hours of work, or to temporary lay-offs (Feldstein, 1976). We find no evidence of labour market failures: labour markets seem to clear in times of shock, with no impact on rates of employment, unemployment, labour force participation or demand for additional labour hours.

Third, we explain our results through a combination of theoretical insights from the implicit contracting literature, and through detailed qualitative work, in the form of focus group discussions that we organised with workers and managers in the aftermath of a recent typhoon. We argue that firms and workers engage in risk sharing in the event of large demand shocks. Workers in long-term employment relationships accept cuts in total wages when shocks hit, while firms insure them against the risk of lay-offs, which would leave them with no income at a time of great need. No layoffs occur if wages are flexible enough, and when firms are relatively indifferent between cutting hours to worker and laying off workers.[2] Qualitative evidence suggests that employment contracts would allow for such flexibility: built on trust, bonus systems introduce profit sharing, which can allow wages to adjust. Workers take a few days work off voluntarily to do repairs but otherwise return to work as normal. There is no evidence of delayed payment. We draw on other literature on the Philippine labour market to explain how cultural norms could sustain such implicit contracting arrangements.

We show that the results are strongest, and exhibit the clearest evidence of downward flexibility, in permanent, non-agricultural private sector wage-paying jobs. The results do not seem to be driven by jobs that are governed by spot markets, which we interpret as wage flexibility within jobs with longer-term relationships that are likely to be governed by implicit contracts.

Fourth, we rule out channels related to changes in sample, workforce or sectoral composition. Our main concern is that migration may have altered the composition of the people for whom we observe wages in typhoon-quarters, which could drive our results.[3] However, show that shocks do not appear to systematically affect the composition of individuals in the sample, the composition of employed individuals or the composition of individuals who report a wage. We find no evidence that storms have an impact on our sample sizes in the months that they fit. Most importantly, we study our panel of individuals that we observe in employment in at least two periods, in the same location. These are individuals that we know have not migrated as result of the shock. We find that, even in this restricted subsample, individuals are no less likely to be employed but that, conditional on working, wages are lower during quarters when storms hit. The results related to wages are robust to further restricting the panel to individuals who are employed in similar jobs and on similar contracts across the sample period. Those results allow us to rule out the possibility that the evidence for downward nominal wage flexibility is driven by changes in sample composition, or in the composition of job types or employment contracts.

Our results have a number of implications for the literature. First, we contribute to a growing literature on the impacts of large natural disasters, particularly those driven by climate change and weather (Dell et al., 2014). Our results suggest that large storms have large impacts on total output in the short run. We estimate that affected municipalities lose 7 per cent of total aggregate income. Yet, contrary to the literature, we find little evidence that these effects persist, perhaps because the labour market develops adaptive mechanisms since such shocks are common.[4]

Second, we contribute to the literature on the identification of wage flexibility during economic shocks. We overcome the econometric challenge of identifying wage flexibility by avoiding problems related to aggregation bias, whereby changes in the composition of the labour force might be driving or dampening changes to nominal wages (Abraham and Haltiwanger, 1995). Panel data allow us to guard against changes in the composition of the sample.[5] Unlike other papers which find evidence of wage rigidity (Kaur, 2014; Holzer and Montgomery, 1993), we find that wages do adjust downwards. This could be due to differences in our setting. Ours is one of the first papers, to our knowledge, to look at wage flexibility, across all wage-paying sectors, in a developing country. Also, the shocks caused by typhoons are unusually large and readily observable.

Third, we contribute to the literature on the effects of implicit contracts on labour market adjustments. The theoretical and empirical literature has focused on long-term labour contracts as a source of inflexibility in labour markets (Azariadis and Stiglitz, 1983; Holmstrom, 1983; Shimer, 2005; Beaudry and Dinardo, 1991; Hall and Milgrom, 2008). Yet, we find evidence that downward wage flexibility is strongest among individuals in long-term, formal sector wage-paying jobs. This suggests that long-term relationships can allow for more flexibility, rather than less.

We argue that our results cannot be driven primarily by shifts in labour supply. We find no evidence that labour supply increases when storms hit, as has been found for farming households that use wage labour markets to smooth income in bad times (Jayachandran, 2006; Kochar, 1999).[6] Yet destruction caused by storms to homes and farms requires time to rebuild (Anttila-Hughes and Hsiang, 2013) and reduces income from non-wage sources. Therefore, we speculate that workers may simultaneously have a greater need for both income and time off work when storms hit. Our finding that there is no change in employment or self-reported labour supply, but reductions in hours and hourly wages, is consistent with our model of implicit contracts. Labour supply elasticity at the intensive margin can be high for individuals who are already working long hours, but highly inelastic at the extensive margin, because workers need their paychecks in the absence of unemployment insurance or good alternatives.[7]

The remainder of the paper is organized as follows. Section II discusses the context and data. Section III establishes that strong typhoons have large but temporary negative effects on labour markets. Section IV discusses the results within a theoretical framework. Section V presents further findings that are consistent with the theoretical framework and rules out alternative mechanisms. Section VI concludes.

II Context and Data

A Typhoons in the Philippines

The Philippines is an ideal setting for our analysis. Typhoons are a regular occurrence and generate large welfare costs (Anttila-Hughes and Hsiang, 2013; Bankoff, 2002; Ugaz and Zanolini, 2011). While data on total damages generated by each storm are available (cf. Table A.54), we need to compute municipality-specific measures of storm exposure. We leverage data from the Japan

Meteorological Agency Tropical Cyclone Database. The database provides information on each tropical storm passing through the North-West Pacific Ocean from 2000 to 2010.[8] The data takes the form of geo-referenced observations at six-hour intervals of each storm's lifespan, including pressure readings and maximum wind speeds for the storm at each point.

The process to compute municipality-specific measures of storm exposure involves three steps. First, for each storm, we apply a model of wind-speed decay to compute the maximum wind speed that affected the municipality (Holland, 1980).[9] Second, using the time-storm data, we assign the wind-speed readings during a storm to one of the three-month periods preceding each of the 26 rounds of employment data described below. Third, we aggregate the measures across the three-month time periods. For each municipality and for each three-month time period, we take the maximum typhoon wind that the municipality was exposed to.

[FIGURE A.2 HERE.]

[TABLE 1 HERE.]

These wind data can then be used to generate various measures of storm intensity by time period according to the Saffir-Simpson classification. This scale classifies hurricane wind speeds into five categories according to the types of damage they will cause. Our main regressions will distinguish between Category 1-3 and Category 4-5 storms. Both Category 4 and 5 storms are said to cause catastrophic damage.[10]

Table 1 gives some indication of the damage caused by the storms in our sample using this system, looking at averages across all municipalities and all time periods. We show the results for all three levels at which we conduct estimation: Municipality, Individual and Panel datasets. The incidence of storms is similar across these datasets. The biggest wind speed experienced was 157 knots (180 miles per hour). On average, 18.8 per cent of the quarterly municipality observations are affected by a tropical storm, but about a third of those are too small to be classified on the Saffir-Simpson scale.[11] Across the country, 23 of the 26 quarters for which we have employment data experienced storms. Fifteen quarters experienced storms that registered on the Saffir-Simpson scale, and nine of those quarters were classified as catastrophically damaging (category 4 & 5). In total 1.6% per cent of our quarterly municipal observations reported very large storms (Saffir-

Simpson category 4 or 5), across 14 different large storms. Importantly, as shown in Figure A.1, the storms are not concentrated in a limited number of quarters.

In Figure A.2 we plot the five typhoons that passed through during September-December 2006, the most active typhoon season during our study period. During this time 18 per cent of municipalities experienced catastrophic damage, and 30 per cent had some experience of typhoons. Storm Chebi (620) clearly registers the greatest damage as it passed through the centre of Luzon, while Storm Durian (621) reached the southern shores of Luzon. The municipalities are coloured according to the Saffir-Simpson score of the biggest storm passing through during the quarter.

B Employment data

We use LFS data collected by the National Statistics Office (NSO) of the Philippines. The surveys are conducted four times a year (January, April, July and October), and we have access to all 26 surveys in the period July 2003 to October 2009.[12] We only use working-age individuals (above 15) and are left with 3.4 million observations.

We use the dataset in three ways. First, we aggregate the individual-level data to build a balanced panel of 1,140 cities and municipalities across the 26 quarters. Second, we use the repeated cross-section of individuals. Third, we extract a panel of individuals from the cross-section. A number of households were interviewed more than once. We then use information on gender, age and education level within households to build a panel of individuals.

A person is considered employed if s/he reported working for at least an hour during the week prior to the survey. In addition, information is collected on the total number of hours worked during the past week, the sector of employment and the daily wage. We compute the employment ratio as a share of the working-age population rather than as a share of the economically active population.[13]

Our main measures of earnings are at the weekly level because the reference period for earnings and hours worked in the survey is over the last seven days. Since we have data on hours, days and total wages over the last seven days, we are able to decompose the effects across hours, days and hourly wages. Further, to understand how the adjustments take place, we also look at the number of days worked and the number of hours per day worked.

Respondents provide three important pieces of data that allow us to compute the following outcomes: (i) Daily earnings; (ii) Average # hours worked per day during the past seven days and; (iii) Total # hours worked during the past seven days.[14] We combine them to compute hourly wage (Daily earnings / Average # hours worked per day during the past 7 days) and weekly earnings (Hourly wage * Total # hours worked during the past 7 days)

[TABLE 2 HERE.]

Table 2 shows the composition of these different jobs in the full individual sample and in the panel. Roughly a third of employed individuals are self-employed (if own-farm workers are included as self-employed), and a little more than a third are employed by private employers. The public sector makes up about 8 per cent of employment. The rest is made up of unpaid family work, which is mostly in agriculture, and domestic work. About half of self-employment jobs are in agriculture, mostly labour on the households' own farm with produce sold for income. Our data do not measure income from self-employment or shadow wages from home production. Most of the income data come from individuals earning wages in the private or public sector.

[FIGURE 2 HERE.]

The individual panel data show considerable variability in individual *nominal* wages. In Figure 2 we plot the distribution of the percentage wage changes for wage-earning individuals in periods when storms do not hit. We compare wage changes for those who stay in jobs with identical employment characteristics (occupation, pay-type, pay regularity, sector) versus individuals whose job characteristics change in any way. Not surprisingly, wages are more variable when workers change jobs, but in most quarters wages do not change at all, even for two wage observations many quarters apart. Large drops in nominal wages are common.

We also collected detailed qualitative data on how firms adjust after typhoons hit and on the relationships between managers and employees. We mobilised a team of researchers from the University of the Philippines in Los Baños to carry out eight FGDs with employees and eight with managers in the province of Camarines Sur in February/March 2017.[15] We selected this area as it was affected by a category 5 super typhoon (Nina) in late December 2016. We take advantage of the wealth of data collected in Sections IV and V.

III Main Results

In this Section we establish that typhoons act as a strong (but temporary) labour demand shock and decompose the effect. We find that large storms lead to large negative effects on wages, through the channel of lower hourly wages and lower hours per worker, with no impacts on total employment. We start with municipal-level analysis and then move to individual-level analyses. In the next section, we build on theoretical insights from the implicit contract literature to explain our results.

A Aggregate results

We start by estimating equations of the form:

$$Y_{mpt} = \alpha S_{mpt} + \beta X_{mpt} + u_{mp} + v_t + w_{mpt} \tag{1}$$

Where Y_{mpt} is the outcome of interest in municipality m in province p at time t, S_{mpt} is a vector of variables capturing whether municipality m has been hit by a typhoon in the previous quarter, X_{mpt} is a vector of municipal characteristics that vary over time, u_{mp} is a municipality-specific unobservable, v_t is a time-specific unobservable and w_{mpt} is the usual idiosyncratic term. Standard errors are clustered at the provincial level.

[TABLE 3 HERE.]

Results, available in Panel A of Table 3, indicate that municipalities hit by a strong typhoon do not experience a change in their employment rate in the quarter following the shock. That is, labour markets do not appear to adjust along the extensive margin. Those results are robust to adding municipal fixed effects (Column 2) and a number of quarter-specific measures of sample composition at the municipal level: education, gender and age (Column 3). We obtain similar results if we exclude municipalities from the southern island of Mindanao (Column 4).[16] This is our preferred set of controls and estimation sample.

Once we focus on income from employment, we find that municipalities experience a large decline in average income in the quarter following the shocks (Panel B of Table 3). The point estimates reported in Column 1 are very large (32 per cent), but once we control for municipal fixed effects (Column 2), the point estimate drops to a still economically significant 6.5 per cent.

This suggests that municipalities that tend to be hit by strong typhoons tend to be disadvantaged, which is consistent with findings by Hsiang and Jina (2014). Once we control for time-varying municipal controls and exclude municipalities from Mindanao the point estimates increase slightly and are still statistically different from zero at the 1 per cent level.

A mechanical concern is that our results might be driven by disruption to survey activities due to the storms. To reduce those concerns, we estimate the impact of storms on wages and employment, excluding all storms that happened in the month of the survey itself, and find similar results (Column 5). If our results were driven by a disruption to surveying activities due to storms, we would expect that the main results would change when dropping these contemporaneous storms.

[TABLE 4 HERE.]

We now decompose the effects on average income and estimate Equation (1) for a number of other outcomes of interest using our preferred specification with municipal fixed effects, time dummies and quarter-specific municipal controls on the non-Mindanao sample. The results are displayed in Table 4. We show that observed average wages fall by 3.6 percentage. This effect can be decomposed into a 2.5 per cent decline in hourly wage and a 1.1 per cent decline in hours worked. To put it differently, at the aggregate level, labour markets adjust by lowering hourly wages and reducing the number of hours worked.

B Individual results

Having established that large typhoons lead to a large aggregate decline in income from employment but have no effects on employment levels, we now explore how firms and their workers adjust to these impacts. Using the full set of individual-level labour force observations, we find results that are consistent with the results in the aggregate data. Average wages decrease after typhoons hit due to the combination of a decline in the hours worked per week and hourly wages. Consistent with our previous results, the effects on unemployment are very small and rarely significant. We show that the small effects on employment that we do find are driven entirely by the self-employed.[17] Employment in wage labour is not affected.

Consistent with the aggregate results, we estimate individual-level equations of the form:

$$Y_{imt} = \alpha S_{mt} + \beta X_{imt} + u_m + v_t + w_{imt} \tag{2}$$

Where Y_{imt} is the outcome of interest for individual i in municipality m i at time t, S_{mt} is a vector of variables capturing whether municipality m has been hit by a typhoon in the previous quarter, X_{imt} is a vector of individual characteristics, u_m is a municipality-specific unobservable, v_t is a time-specific unobservable and w_{int} is the usual idiosyncratic term. Standard errors are clustered at the municipal level. As above, we first estimate Equation (2) without any controls, then add time dummies, municipal fixed effects and individual controls (education, age, age squared and gender).

[TABLE 5 HERE.]

Individual-level results, available in Table 5, are consistent with the aggregate results discussed above. Typhoons do not affect the probability of being employed, but average wages for employed individuals are 2.1 per cent lower in post-storm quarters. The results are robust to dropping the province of Mindanao (Column 4), and to dropping the months in which the survey took place in the same month as any large storm hit (Column 5).

[TABLE 6 HERE.]

As above, we can decompose the effect of typhoons on average income (Table 6). In the quarter after the storm, individuals report working one per cent fewer hours (Column 2), although this effect is not significant. Hourly wages are significantly lower, by 1.4 percent (Column 4). These two effects combined lead to the overall impact on wages in Column 1. We see a half percentage point effect on total employment, which is marginally significant, and a similar (insignificant) effect on days worked per week.

C Robustness

We now check that our results discussed so far are robust before explaining our results in the context of implicit contracts. We explore robustness along multiple dimensions. These results are presented in the online appendix but summarized briefly here. First, we show that our results are not driven by a specific choice of parameter values used to compute our storm measures. We re-estimate our results at the aggregate- and individual- level using permutations of both the smoothing and radius parameters, both above and below the choice in our preferred specification. These results are summarized for employment and earnings in Tables A.1 and A.2, and all decompositions are replicated in Tables A.3—A.20.[18] Second, we show that our results are not driven by any specific storm by dropping one large storm at a time from our sample for both the aggregate (Table A.21) and individual (Table A.22) results. Importantly, we are unable to reject the null that the point estimate in the weekly wage equation on each of those samples is different from the point estimate on the full sample (the z-stats are between -.32 and .22). Third, our results are robust to using alternative measures of storm strength, in particular, wind speed in knots and normalized wind speed (Tables A.23 and A.24). Fourth, wide storms - hitting more municipalities at once - do not appear to drive our results (Table A.25). Fifth, slow moving storms - which could be more destructive as they spend more time on each municipality - do not generate larger effects (Table A.26). Sixth, we find no evidence that municipalities that were hit more often, during the duration of our study, suffered more from the large storms (Table A.27). Seventh, to deal with concerns that household members may report inaccurate information about other household members' salaries, we show that our results are robust to looking at the impacts on wages of household heads only, who are most likely to be the primary respondent in the survey (Table A.28). Again, we are unable to reject the null that the point estimate in the weekly wage equation on the sample of household heads is different from the point estimate on the full sample (z-stat= -.73). Finally, in Table A.30 we show that results are not driven by changes in sample size: we find no impact of small or big storms on the number of households, people, or adults surveyed in each municipality.

D Persistence

A potential concern with our results is that they only focus on short-term impacts of the storm and might fail to capture more relevant longer-term impacts. We now estimate Equation (1) including lagged values of the shock variables. The results, displayed in Table 7, confirm our modelling choice. Storms do not appear to affect labour markets after one quarter. For example, when focusing on our main measures of economic activity, the point estimate of the shock measure lagged once is 60 per cent lower than it is for the current version of the shock and is no longer statistically significant. There is a similar pattern for other outcomes of interest: the lagged term is more than 50 per cent lower for average wages and almost 80 per cent lower for average hourly wages. We are not always able to reject the null that the estimated effects of the current value and the first lag are equal, but once we look at the second and third lags, the results confirm that the impacts of storms on labour markets are short-lived. From now on we focus on the current impacts of storms.

[TABLE 7 HERE.]

IV Theoretical Framework and Context

In this Section, we discuss a theoretical framework that explains our results and can guide further empirical analysis. We also provide evidence in support of its main assumptions. The evidence comes from existing literature on Philippine labor markets and from FGDs that we organised with both managers and employees in the province of Camarines Sur in February/March 2017. We selected this area as it was affected by a category 5 typhoon (Nina) in late December 2016. The model is presented in the Online Appendix.

Recall that workers in areas affected by strong typhoons experience reductions in their wages, without evidence of layoffs. We have in mind a mechanism whereby storms cause the destruction of working capital and inventory, and disruption to retail activities, leading to a reduction in marginal revenue product of labour. Firms would like to hire less labour and to pay workers less, especially if they are credit constrained. Profit sharing arrangements make it possible for firms to reach those outcomes by paying higher total wages when economic activity returns to normal.

We aim to explain those results through a model of implicit contracts. Under such contracts, workers and firms share risks when shocks to the firm occur (Baily, 1974; Azariadis, 1975). Miyazaki and Neary (1985) and Rosen (1985) extend the basic model to allow for flexibility in the intensive margin of labour (hours per worker) and the extensive margin (layoffs), in which workers may prefer to work fewer hours and receive lower pay, rather than risk being laid off. Risk-averse workers are further compensated for low pay in bad states with higher wages in normal states.

According to the model, flexibility in working arrangements after shocks is efficient. Negative shocks are more likely to lead to a reduction in hours worked and wages but no increase in unemployment under the following conditions. First, when workers' outside options after negative shocks are worse, they are more likely to accept the lower wages offered by firms to avoid unemployment. Second, the contractual environment needs to be flexible enough to allow these changes in wages. Third, the risk-sharing mechanism we have in mind requires trust between managers and workers which is more likely to be present when they are engaged in reciprocal relationships. Finally, the shocks need to be observable for state-contingent contracts to be enforceable.

We now discuss, with the use of data from our FGDs and existing literature from the Philippines, evidence that our setting supports such flexible relationships. Despite being hit by a category 5 typhoon, managers reported not laying-off workers, but lowering their working hours. We also describe some specific contracting mechanisms that might allow for wage flexibility, without workers and firms setting explicit wage schedules based on the arrival of typhoons.

First, there is significant evidence that typhoons have a direct negative impact on firms' productivity and workers' outside options. Managers who participated in our FGDs report that typhoons generate losses of stocks and inventories of raw materials as well as difficulties in purchasing inputs. Importantly, typhoons also severely disrupt electricity supply and negatively affect sales.[19] Given that firms are trying to reduce their wage bill, it is likely that workers face lower labor demand overall. Similarly, Anttila-Hughes and Hsiang (2013) show that the agricultural sector is negatively affected by typhoons.

Second, we find evidence for risk sharing between employers and workers. Managers in our FGDs report that workers are paid extra for overtime (up to 30 percent) and receive bonuses when sales are high. This suggests that total wages vary with firm profit. Recall that the effects of storms are not persistent; wages return to normal after just one quarter. This is consistent with the notion of implicit compensation that workers get for firms lowering their hours and wages when shocks hit. This is not consistent with a mechanism whereby firms simply delay payment until cash flow improves, as this would imply that total wages go up after the storms. FGD participants - both managers and workers - confirmed that firms do not delay payments when typhoons hit. Firms report that they understand that during storms workers may have especially acute needs for timely wage payments for daily living. Firms say that they rely on firm savings to cover salaries during storms.

How are flexible wage schedules implemented in practice? In our focus groups, while most workers reported being "regular" (*i.e.,* in long-term employment relationships), they do not have written contracts. This allows managers to adjust their workers' schedule at short notice and some of them report doing so based on demand. Workers and managers are often engaged in long-standing relational contracts. Two Filipino cultural traits make cooperation in those contracts more likely to be sustained: (i) *utang na loob*, which refers to a debt of gratitude that fosters reciprocity and feelings of social obligation; and (ii) *hiya*, which refers to the stigma associated with not fulfilling one's social obligations (Cruz et al., ming). In our qualitative fieldwork, workers indicated that they value good relationships with their managers and that it is one of the main reason why they are staying with their current employer. The majority of workers are hired through friends and relatives of the managers or current employees. This increases the likelihood that cooperation will be sustained (Jackson et al., 2012). Another cultural trait increases managers' incentives to retain workers: *pakikiisa* (feeling of oneness), which refers to a sense of shared purposed and solidarity. It takes time to build. This is consistent with finding by Amante (1995, 1997) who argue that Filipino employers value both loyalty and flexibility.

Finally, Rosen (1985) writes that implicit labour contracts should specify 'precisely the amount of labour to be utilized and the wages to be paid in each state of nature, that is, conditional on information (random variables) observed by both parties.' Storms are easily observable and can be contracted upon.

V Long-term employment contracts and downward wage flexibility

We present evidence that flexibility arises in established contractual employment relationships, with strong effects observed for individuals employed on permanent contracts in the private sector, which we interpret as being consistent with the implicit contract model introduced in Section IV. Specifically, we show that the effects are not driven by spot markets. We also show that the effects are not driven by changes in sample composition (including migration), sectoral reallocation, or labour supply. We discuss further qualitative evidence on the role of labour supply of workers.

A Wage employment in the private sector

We provide evidence consistent with the argument that downward wage flexibility is driven by wage flexibility within wage employment contracts. First, we estimate Equation (2) but interact the storms variable (and all other control variables) with a dummy equal to 1 for individuals in wage employment in the private sector (on either permanent or temporary contracts). Results are available in Panel A of Table 8. Interestingly, the base effect suggests that there is no impact of storms outside the private sector, but the interaction term indicates that weekly wages in the private sector decrease by 4.2 percent in the post-storm quarter. While workers outside the private sector experience a reduction in the number of hours worked, private sector workers experience a reduction in their hourly wage.

[TABLE 8 HERE.]

In addition, we restrict the sample to workers in wage employment in the private sector and compare the effects for individuals employed on temporary vs. permanent contracts. Overall, we are unable to reject the possibility that the effects on weekly wage are the same, but the adjustment margins differ greatly (Panel A of Table 8). Indeed, while individuals on temporary contracts reduce the number of hours worked (mostly by reducing the number of days worked), individuals on permanent contracts do not adjust their hours but experience a 2.6 percent reduction in their hourly wage.

The evidence suggests that the results are different between temporary and permanent jobs. Most strikingly, permanent jobs exhibit considerable downward flexibility in *hourly* wages. There is relatively little adjustment in hours worked per paid worker (Column 3). The weekly wage adjustment for temporary jobs is not significantly different from that in permanent jobs, but the results seem to be driven by a fall in the number of hours worked rather than by a fall in the hourly wage.

This evidence suggests that even long-term permanent contract agreements exhibit high levels of flexibility. These findings are consistent with the implicit contracts model discussed in Section IV. Therefore, we do not believe that our mains results are driven by the operation of spot markets. Conversely, results for temporary forms of employment are consistent with the behaviour of a spot market, with highly elastic labour supply: workers reduce the number of days worked. No lay-offs occur for either type of jobs.

B Alternative channels

The results discussed so far suggest that nominal wages exhibit significant downward flexibility when a typhoon hits as a result of implicit contracts between workers and firms. We now address alternative mechanisms, including sample composition, sectoral reallocation and substitution.

1 Are the results driven by changes in sample composition?

We take advantage of the availability of panel data and show that the results are similar for individuals in the panel dataset. By construction, this set of analyses keeps the sample constant.[20] We estimate Equation (2) on the panel described in Section II.B. Panel A of Table 9 shows the main results for the individual panel sample. Wages fall by 2.4 percent and there is no evidence that the probability of being employed is affected by the timing of typhoons (Tables 9 and A.32).[21] We are unable to reject the null that the point estimate in the weekly wage equation is different from the point estimate on the full sample (z-stat= .22). Again, the results seem to be driven by a combination of significant drops in hours per worker and in the hourly wage (1.9 percent).

[TABLE 9 HERE.]

We further clarify why panel data are especially useful in our context. First, while Keane et al. (1988) have suggested that the use of panel estimators does not fully address the problem of selection bias, we argue that their concerns are less valid in our case. Their argument is that if high-skilled individuals in the panel are less likely to be employed in quarters when storms hit, this could lead to the impression that wages are flexible downwards. However, this problem arises in a setting in which changes in unemployment are used as the dependent variable; by definition, these estimators examine situations with a lot of movement out of the labour force. However, this is unlikely to explain our results, as we found no evidence that storms affect the probability of being employed or of being engaged in different types of wage-paying work conditional on being employed (Table A.34). Furthermore, we restrict our sample of panel observations to individuals who we observe working in at least two periods. The vast majority of individuals are observed in the panel only twice. By looking at the sample of individuals who were earning in both of those periods of the panel, we clearly document changes in their wages between the two periods.

Second, the panel data helps us deal with concerns related to aggregation bias due to migration since we observe reductions in wages for individuals who have not migrated. Some workers might migrate as a result of shocks but, if migration was driving our results, the results should not hold in the panel.

Further, we check that changes in observable characteristics of respondents in the individual cross-section is not affected by storms. We estimate Equation (2) regressing the individual-level characteristics for which we have data (education, age and gender) on the full set of municipal and time fixed effects and the storm dummies. We estimate each of those equations on the full sample, on the sample of employed individuals and on the sample of wage earners. The results, available in Table A.47, do not suggest that the timing of typhoon occurrence affects the sample composition. Among the 24 tests carried out (gender, age and six education categories on the three samples), we only reject the null three times and the point estimates are small in magnitude. Employed individuals are slightly more likely to be graduates from primary school in the quarters in which storms hit, but this increase is driven by insignificant decreases in composition of lower and higher education levels. These results are not robust to alternative storm parameterizations.

2 Are the results driven by sectoral reallocation?

Economic shocks like those caused by large natural disasters can have large impacts on the composition of employment in affected areas, and can change the sectoral composition of economic activities (Moretti, 2010; Kirchberger, 2014). If the storms studied in this paper caused sectoral shifts toward lower-paying industries and jobs, this could be driving the effects on average wages. While this appears unlikely since the effects discussed so far are short-lived, here we show that the overall composition of jobs did not change in the full individual sample.

Panel A of Table A.49 shows the impacts of storms on the probability of a working individual being employed in a particular type of job. Storms affect only one category of work: individuals are marginally significantly less likely to be engaged in public sector work when storms hit, although the coefficient is small. Aside from the effect on the public sector, Panel B of Table A.49 shows that the composition of jobs across wage paying forms of employment is unaffected by storms.

Panel C of Table A.49 reproduces the analysis on the sample of individuals earning a wage. Again, we find that wage earners are very slightly less likely to work in the public sector.

We are confident that these small changes are not driving our main results.[22] Overall, we interpret this set of results to indicate that the decline in nominal wages observed in the quarter after storms hit is not driven by sectoral reallocation. Note that, once we focus on the panel of individuals who we observe more than once in the data, there is no evidence that storms affect the sectoral composition of jobs in this subsample (Table A.34).

3 Are the results driven by job switches?

A related concern is that individuals who stayed in the panel might have switched to different job types. As above, this would generate our results without any worker experiencing a drop in hours or income within the same job. We estimate Equation (2), further restricting the sample to individuals who stay in similar job types throughout the sample period.[23] The results, available in Panel B of Table 9, confirm that even in this restricted sample workers experience a short-term drop in both hours worked and hourly wages. Again, we are unable to reject the null that the point estimate in the weekly wage equation is different from the point estimate on the full sample (z-stat= -.4)

A final concern is that individuals who did not move and stayed in similar job types might have renegotiated their contracts – for example, by switching from permanent to temporary contracts. To address those concerns, we restrict the sample to individuals who stayed in similar job types and similar contract types and estimate Equation (2) on this subsample. These individuals also remain on the same payment schedule (monthly payments, daily payments or pay on commission). Again, results available in Panel B of Table A.35 confirm our earlier results.

4 Labour supply response

We now rule out the possibility that our results are driven by changes in labour supply. This is important, as Jayachandran (2006) finds that large agricultural productivity shocks cause shifts in labour supply away from farm work *towards* wage labour, which in turn accounts for large reductions in wages. Similarly, Kochar (1999) shows that the hours worked increase in rural areas as rural households attempt to smooth consumption during shocks.

In Panel A of Table A.51, we show that storms have no impact on various measures of labour supply. Respondents are no less likely to report being in the labour force (Column 1), no more likely to be searching for work (whether employed or not), and no more likely to be looking for work while unemployed. Also, there is no increase in the probability that an employed individual will want more work (Column 5) or have searched for additional work (Column 6). This provides strong evidence that large labour demand shocks do not result in wage rationing: labour markets seem to clear in the wake of large shocks. In Panel B of Table A.51 we confirm that this holds for the sample that stayed in the individual panel, with the coefficients following much the same pattern as in the individual data. This result is important: the analysis of wages in the panel data focused on wage earners who were observed for at least two periods.

Labour markets seem to clear at both the extensive margin (no rise in unemployment) and the intensive margin (no rise in underemployment as measured by a demand for additional hours of work). This is consistent with the qualitative evidence that we gathered through our FGDs. Managers report that some workers require a couple of days off in the immediate aftermath of the storms to repair their homes. In any case, this is not driving our results which our robust to dropping observations where the storm hit in the month of the survey. Once this is done, workers return to work with normal hours. In some cases, workers are asked to work on important repairs to facilities rather than on regular productive activities. Finally, workers in FGDs report that reduction in work hours are determined by managers.

VI Conclusion

In this paper, taking advantage of a unique individual-level labour force dataset spanning 26 quarters between 2003 and 2009, we explore how labour markets adjust to large economic shocks, namely strong typhoons. Our results suggest that employment levels are unaffected but nominal weekly wages adjust downwards, through a combination of lower hours and lower hourly wages. The effects are driven by individuals employed on permanent contracts in the private sector and dissipate shortly after the storms hit.

The results have implications for our understanding of labour markets in developing countries. First, there is evidence of flexibility in established long-term contractual relationships, which is consistent with theories of implicit contracts. Second, the adjustments take place along the intensive rather than extensive margin, which we interpret as risk sharing between the firms and the workers. This built-in insurance mechanism seems to indicate sophisticated informal arrangements for coping with large economic shocks. In contexts where social safety nets might be inadequate, utility loss associated with unemployment is likely large, and it appears that considerable risk sharing occurs between firms and workers. Third, our results are obtained in a context in which typhoons are relatively common, and so could be thought of as an adaptive response to repeated natural disaster shocks.

Notes

[1]Since we are interested in the total wages that firms pay workers, our preferred measure is weekly wage income, as this is the highest level of aggregation over time that we can use.

[2]In the model, layoffs are also less likely to happen when labour is relatively indivisible: that is when the marginal return to adding labour hours to the existing workforce is not considerably larger that it is for adding to the total number of works.

[3] Typhoons may very well have induced out-migration (Kleemans and Magruder, 2012; Gröger and Zylberberg, 2015).

[4]Our findings do not estimate the impact of storms on growth trajectories or other long-term outcomes, because of our use of municipal fixed effects, time fixed effects and quarterly data. Our results without municipal fixed effects suggest that municipalities that are regularly hit are poorer than areas that are not (although these findings are not necessarily causal). Therefore our findings do not conflict with the growing body of evidence showing that natural disasters have long-term consequences for economic growth and household well-being (Anttila-Hughes and Hsiang, 2013; Hsiang and Jina, 2014).

[5]Keane et al. (1988) also use panel data. By contrast, Kaur (2014) argues that evidence of asymmetric responses to positive and negative shocks is inconsistent with the possibility that the results are driven by labour supply and sample composition changes.

[6]This difference is likely explained by (i) the nature of shocks in our sample, which are not only agricultural and thus affect labour demand in the wage sector and (ii) the fact that typhoons cause the kind of catastrophic damage that requires homes to be rebuilt.

[7]This is contrary to evidence from OECD countries, where changes in employment rates account for most fluctuations in total hours worked (Rogerson and Shimer, 2011).

[8]These data can be accessed online at http://www.jma.go.jp/en/typh/, last accessed on 1 December 2012.

[9]We start by generating best-fit lines through the six-hourly observations to mimic the storm path. Then for each municipality, we calculate the distance to every storm in the dataset, recover the storm track point to which it is closest, and the corresponding storm pressure (in hPa) at the moment when the storm passed over the municipality. We then estimate wind speeds for each municipality–storm combination (Holland, 1980). The model uses the distance from the eye of the storm and the pressure at the eye to calculate a wind speed at any point. We discuss our parameter choices in the Online Appendix and show that our results are robust to alternative parametrizations.

[10]The latest version of Saffir-Simpson hurricane classifications is outlined by the National Oceanic and Atmospheric Administration's (NOAA) National Hurricane Center, available online at http://www.nhc.noaa.gov/aboutsshws.php, last accessed on 1 December 2012. According to NOAA, it is expected that after a Category 5 storm, 'a high percentage of framed homes will be destroyed, with total roof failure and wall collapse. Fallen trees and power poles will isolate residential areas. Power outages will last for weeks to possibly months. Most of the area will be uninhabitable for weeks or months'.

[11]Many wind speeds generated in this way are negligibly small and can be safely dropped because the storm passed too far from the municipality to register an impact. We ignored all storms not registering on the Saffir-Simpson scale (that is, those not reaching wind speeds above 60 knots).

[12]More information on the survey design is available at: http://www.census.gov.ph/data/technotes/notelfs_new.html visited on 26 March 2012.

[13]As discussed in Labonne (2016), the definition of the economically active population changed in April 2005, so it is not possible to compute the employment rate as a share of the economically active population consistently across survey waves. The information required to adjust past series is not available. However, the definition of employment has not changed.

[14]The measure of daily earnings is derived differently according to how someone is paid. For workers who are paid on an hourly basis, the daily rate is computed as their hourly rate multiplied by average working hours (per day) over the past week. For workers who are paid monthly, the daily rate is computed as their monthly wage divided by the number of working days per month.

[15]The number of FGDs is consistent with recommendations by Guest et al. (2017)

[16]Typhoon incidence increases with latitude in the Philippines and, historically, Mindanao has very rarely been hit by typhoons. No municipality in Mindanao was hit by either a small or a large typhoon during the sample period, and since employment patterns might be different there, we prefer to exclude those observations from the sample as they do not contribute to the estimation of α.

[17]This finding is in line with previous studies on the effects of typhoons in the Philippines (Anttila-Hughes and Hsiang, 2013).

[18]The original version of the paper used a different paramaterization and, for completeness, those results are available in Tables A.40 –A.53.

[19]One of the managers interviewed indicated that average daily sales went from PHP 21-25k (USD 420-520) before the typhoon to PHP 6k (USD 120) after the typhoon.

[20] Importantly, on average, individuals observed more than once do not appear to systematically differ from the rest of the sample (Table 2). This mitigates concerns about the representativeness of the panel data.

[21]Given that the outcomes we are interested in are persistent and subject to measurement error, we do not estimate an individual fixed-effects model, although the main results are robust to the use of individual fixed effects in these regressions (see Table A.33 in the Appendix).

[22] As we show in the sectoral analysis in Section IV, the impacts on income are driven by wage changes in the private sector: the results hold even when public sector work is removing from the estimation. Self-employed wages are not observed in this data: 99 per cent of all self-employed individuals have their wages reported as missing, and the data does not allow us to impute income from self-employment. Finally, we find that these results on public sector work on are not consistent across paramaterization, they do not show up when we permute our chosen parameter selection (see, for example, Table A.50).

[23]The data do not allow us to distinguish between workers who have switched jobs and those who have remained in the same job since the last quarter.

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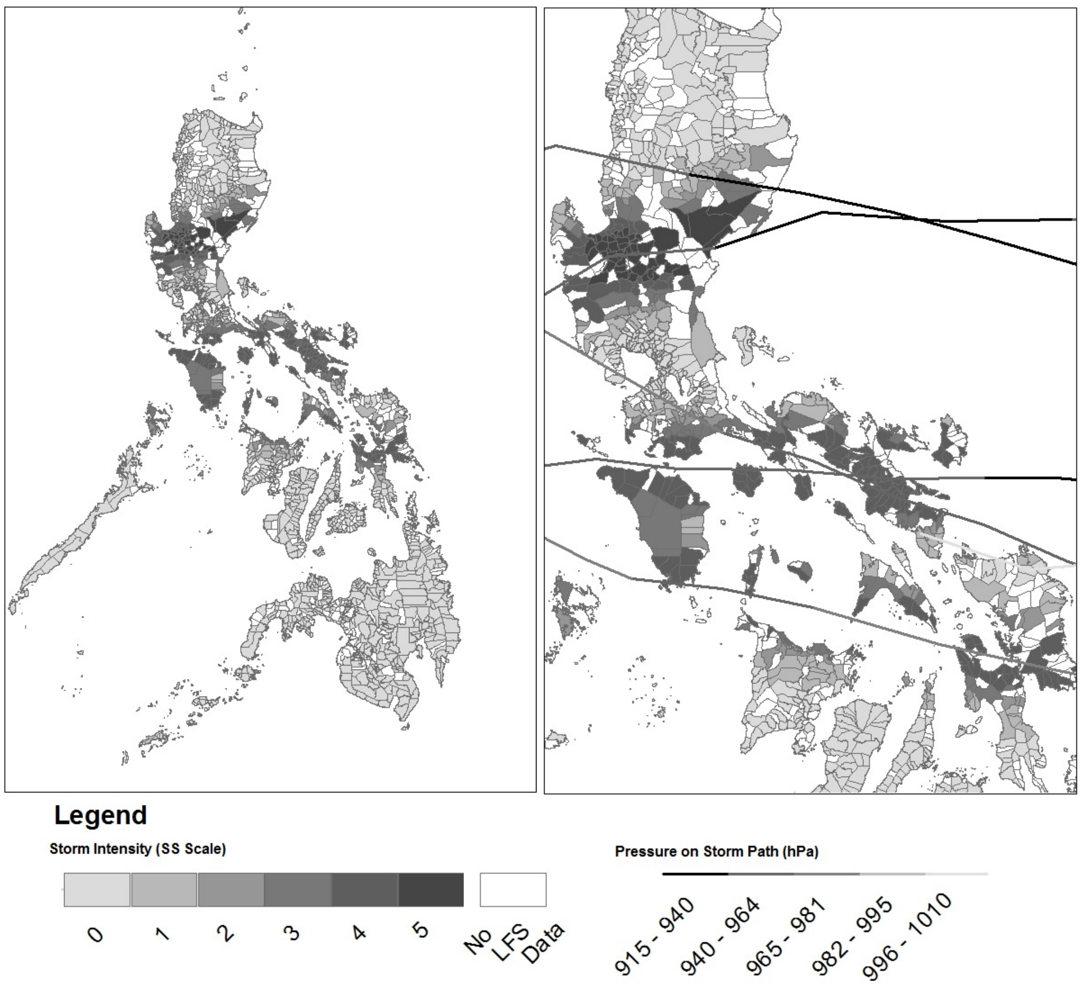
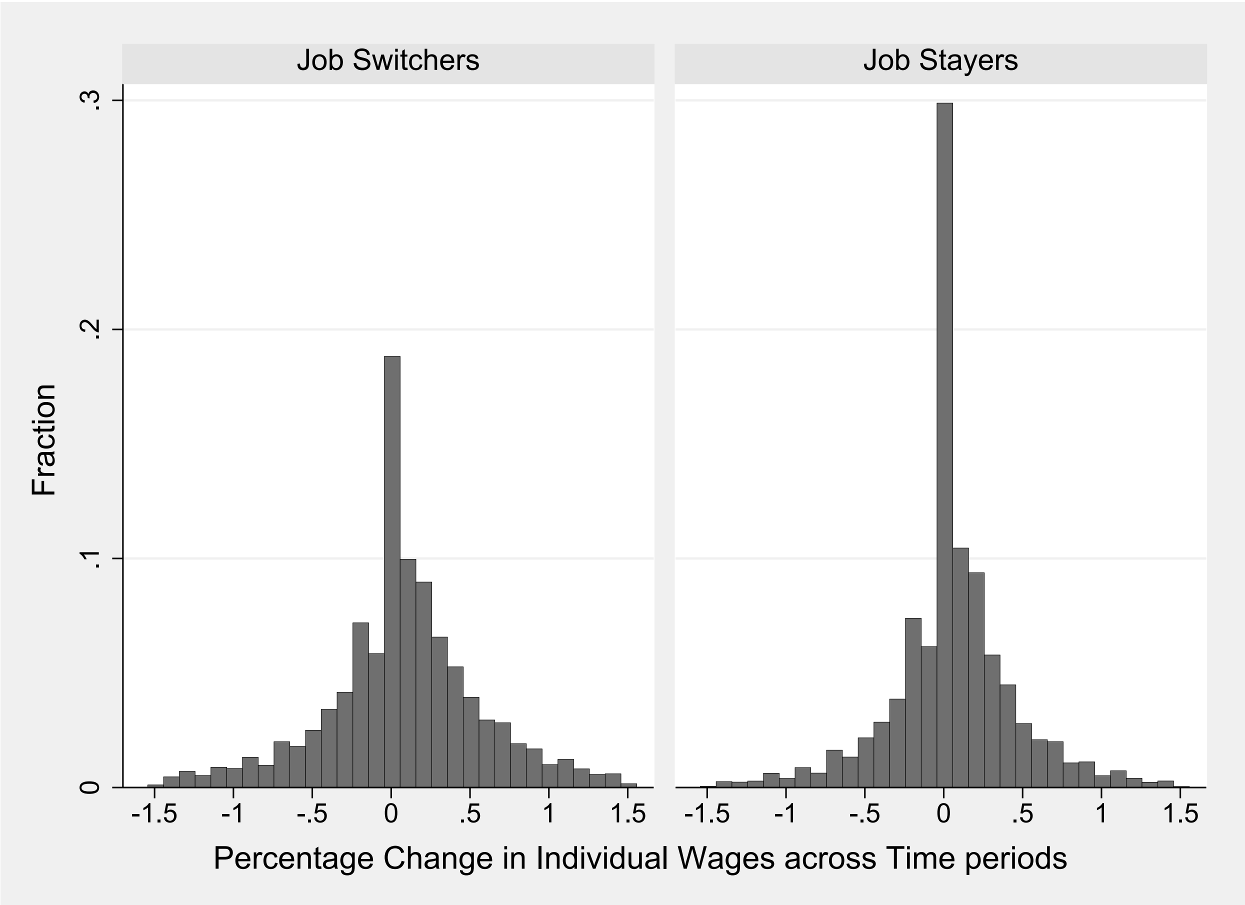
Figures

Figure 1: Storm damage by municipality (Sept-Dec 2006)



Color version available in the online appendix

Figure 2: Percentage in wage changes for individuals in the panel data who switch jobs and those that stay in the same jobs (periods without storms)



Tables

Table 1: Average municipality storm measures across all quarters (2003-2009)

Data Source	Municipality N= 21,064		Individual N=2,538,621		Panel N= 1,873,674		
Measure	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Max
Max Windspeed	13.036	31.11	13.24	31.30	11.06	29.35	157.92
Standardized windspeed	0.0295	0.0978	0.0300	0.0981	0.0261	0.0957	1
Any storm-wind detected	16.93%	37.50%	17.18%	37.72%	14.17%	34.88%	1
Storm on SS-Scale	11.10%	31.41%	11.32%	31.68%	9.22%	28.93%	
SS class-0	88.90%	31.41%	88.68%	31.68%	90.78%	28.93%	
SS class-1	3.36%	18.02%	3.44%	18.23%	2.52%	15.67%	
SS class-2	2.29%	14.96%	2.34%	15.11%	2.03%	14.10%	
SS class-3	3.80%	19.13%	3.91%	19.38%	2.84%	16.61%	
SS class-4	1.38%	11.68%	1.38%	11.65%	1.56%	12.39%	
SS class-5	0.26%	5.11%	0.26%	5.07%	0.27%	5.21%	
Big Storms (SS -4&5)	1.64%	12.72%	1.63%	12.68%	1.83%	13.41%	
Small Storms (SS -1, 2&3)	9.45%	29.26%	9.69%	29.58%	7.39%	26.15%	

Table 2: Descriptive statistics: Individual data

Variable	Full Sample			Panel		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
Income per capita (PHP)	383.6	(1122.1)	3,411,277	378.7	(1106.8)	1,835,793
Average Wage (PHP)	1402.5	(1781.7)	882,109	1401.6	(1760.9)	468,336
Hours per worker	40.8%	(19.4)	2,048,189	40.1%	(19.2)	1,158,032
Employed	58.3%	(49.3)	3,411,277	61.3%	(48.7)	1,835,793
Unemployed	5.6%	(23.0)	3,411,277	5.0%	(21.9)	1,835,793
No schooling	2.2%	(14.8)	3,411,277	2.3%	(15.1)	1,835,793
Some primary	14.3%	(35.0)	3,411,277	15.4%	(36.1)	1,835,793
Primary graduate	14.9%	(35.6)	3,411,277	15.8%	(36.4)	1,835,793
Some secondary	17.3%	(37.8)	3,411,277	16.1%	(36.7)	1,835,793
Secondary graduate	24.2%	(42.8)	3,411,277	23.9%	(42.6)	1,835,793
Some college	27.1%	(44.5)	3,411,277	26.6%	(44.2)	1,835,793
Female	0.5%	(0.5)	3,411,277	0.5%	(0.5)	1,835,793
Age	35.8%	(16.3)	3,411,277	37.4%	(15.9)	1,835,793
	Composition of jobs					
Wage employment	51.7%	(50.0)	2,014,839	48.9%	(50.0)	1,139,465
Agriculture	34.8%	(47.6)	2,014,839	37.5%	(48.4)	1,139,465
	Key Job Types					
Own farm	26.2%	(44.0)	2,014,839	28.6%	(45.2)	1,139,465
Wage farm	8.6%	(28.0)	2,014,839	8.9%	(28.5)	1,139,465
Self employed	22.1%	(41.5)	2,014,839	22.5%	(41.7)	1,139,465
Government	7.7%	(26.6)	2,014,839	8.1%	(27.3)	1,139,465
Private permanent	26.5%	(44.1)	2,014,839	23.8%	(42.6)	1,139,465
Private temporary	9.0%	(28.6)	2,014,839	8.1%	(27.2)	1,139,465

Table 3: Aggregate-level results

	(1)	(2)	(3)	(4)	(5)
Panel A: Impact on Employment Rate per Adult					
Big Storm	0.019	-0.004	-0.004	-0.005	-0.005
	(0.012)	(0.004)	(0.004)	(0.004)	(0.005)
Small Storm	-0.013*	0.001	0.001	0.002	0.002
	(0.008)	(0.002)	(0.002)	(0.002)	(0.003)
Observations	29,560	29,560	29,560	21,064	19,443
R-squared	0.006	0.011	0.017	0.021	0.022
Mean Dep. Var	0.600	0.600	0.600	0.600	0.600
Panel B: Impact on Log Income per Adult					
Big Storm	-0.327***	-0.052***	-0.061***	-0.067***	-0.090***
	(0.085)	(0.017)	(0.017)	(0.018)	(0.020)
Small Storm	0.230***	0.006	-0.001	-0.007	-0.021*
	(0.071)	(0.009)	(0.009)	(0.009)	(0.011)
Observations	28,608	28,608	28,608	20,808	19,200
R-squared	0.018	0.051	0.061	0.073	0.077
Mean Dep. Var	5.300	5.300	5.300	5.400	5.400
Mun FE	No	Yes	Yes	Yes	Yes
Agg Contr	No	No	Yes	Yes	Yes
Mindanao Incl.	Yes	Yes	Yes	No	No
Storm survey	Yes	Yes	Yes	Yes	No

Notes: Results from weighted municipal*quarter regressions. The dependent variable is the employment rate in the municipality (Panel A) and the average wage in the municipality (Panel B). Regressions control for time fixed effects (Column 1-4), municipal fixed effects (Column 2-4), as well as the share of the working age population in each education category, the share of women in the working age population, the number of men, the number of women, the number men age 15-30 and the number of women age 15-30 (Column 3-4). In Column 4, the sample is restricted to municipalities outside of Mindanao. Column 5 drops all time periods where a super typhoon hit the country (any municipality) in the same month that the labour force survey was being conducted. The standard errors (in parentheses) account for potential correlation within province. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table 4: Decomposing the aggregate-level effects

	(1) inc/ adult	(2) wage/ week	(3) wage/ hour	(4) hours/ earner	(5) earners/ job	(6) job/ adult
Big Storm	-0.067***	-0.036***	-0.025***	-0.011	-0.023	-0.008
	(0.018)	(0.011)	(0.009)	(0.009)	(0.017)	(0.006)
Small Storm	-0.008	-0.014**	-0.010*	-0.003	0.003	0.002
	(0.010)	(0.007)	(0.005)	(0.004)	(0.008)	(0.003)
Denominator	Adults	Earners	Earned Hours	Earners	Jobs	Adults
Observations	20,808	20,808	20,808	20,808	20,808	20,808
R-squared	0.073	0.131	0.146	0.068	0.024	0.016

Results from weighted municipal*quarter regressions. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). Regressions control for municipal fixed effects, time fixed effects as well as the share of the working age population in each education category, the share of women in the working age population, the number of men, the number of women, the number men age 15-30 and the number of women age 15-30. The sample is restricted to municipalities outside of Mindanao. The standard errors (in parentheses) account for potential correlation within province. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table 5: Individual-level results: Impacts on wages and employment

	(1)	(2)	(3)	(4)	(5)
Panel A: Impact on Employment per Adult					
	employed	employed	employed	employed	employed
Big Storm	0.018***	-0.004	-0.004	-0.005*	-0.004
	(0.007)	(0.003)	(0.003)	(0.003)	(0.004)
Small Storm	-0.014***	0.001	0.001	0.002	0.002
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	3,402,456	3,402,456	3,402,456	2,464,172	2,271,302
R-squared	0.000	0.023	0.228	0.219	0.220
Mean Dep. Var	0.600	0.600	0.600	0.600	0.600
Panel B: Impact on Log of Wages					
	wage/ week	wage/ week	wage/ week	wage/ week	wage/ week
Big Storm	-0.223***	-0.016	-0.018**	-0.021**	-0.028**
	(0.038)	(0.011)	(0.009)	(0.009)	(0.013)
Small Storm	0.142***	0.002	-0.001	-0.004	-0.006
	(0.022)	(0.006)	(0.005)	(0.005)	(0.006)
Observations	860,809	860,809	860,809	660,650	607,754
R-squared	0.013	0.216	0.444	0.446	0.446
Mean Dep. Var	6.900	6.900	6.900	7.000	7.000
Mun FE	No	Yes	Yes	Yes	Yes
Agg Contr	No	No	Yes	Yes	Yes
Mindanao Incl.	Yes	Yes	Yes	No	No
Storm month	Yes	Yes	Yes	Yes	No

Notes: Results from weighted individual regressions. The dependent variable is a dummy equal to one if the individual is employed (Panel A) and log of wages for employed individuals (Panel B). Regressions control for time fixed effects (Column 1-4), municipal fixed effects (Column 2-4), as well as the respondent's age, age square, education levels and gender (Column 3-4). In Column 4, the sample is restricted to municipalities outside of Mindanao. Column 5 drops all periods in which a Super Typhoon hit in the same month as the survey was being conducted. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table 6: Individual-level results: decomposition

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact on Intensive Margins (Earnings and Hours)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.021**	-0.010	-0.007	-0.014**	-0.006	-0.001
	(0.009)	(0.008)	(0.007)	(0.007)	(0.006)	(0.004)
Small Storm	-0.004	-0.006	-0.002	-0.002	0.001	-0.004*
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	660,650	1,430,357	660,650	660,650	660,650	660,650
R-squared	0.446	0.128	0.094	0.417	0.093	0.039
Panel B: Impact on Extensive Margins						
	employed	job	wage missing	wage observed	zero hours	lost job quarter
Big Storm	-0.005*	-0.004	0.005	-0.005	0.001	0.001
	(0.003)	(0.003)	(0.005)	(0.003)	(0.001)	(0.002)
Small Storm	0.002	0.002	-0.001	0.002	0.000	-0.003***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)
Sample	All	All	Earners	All	All	All
Observations	2,464,172	2,464,172	1,430,353	2,464,172	2,464,172	2,464,172
R-squared	0.219	0.228	0.188	0.097	0.015	0.021
Mean Dep. Var	0.573	0.581	0.507	0.286	0.009	0.030

Notes: Results from weighted individual regressions. In Panel A, the dependent variable is the log weekly wage for employed individuals (Column 1), number of hours worked for employed individuals (Column 2), number of hours worked for employed individuals earning a wage (Column 3), hourly wage for employed individuals (Column 4), number of days worked for employed individuals earning a wage (Column 5), number of hours worked per day for employed individuals earning a wage (Column 6). In Panel B, the dependent variables are a series of dummies equal to one if: the individual is employed (Column 1), the individual has a job (Column 2), the individual is employed but their wage is not observed (Column 3), the individual reports a wage regardless of employment status (Column 4), the individual reports having a job but working zero hours in the last 7 days (Column 5), the individual reports not having a job now, but having worked in the last 3 months (Column 6). Regressions control for municipal fixed effects, time fixed effects as well as respondent's age, age square, education levels and gender. The standard errors (in parentheses) account for potential correlation within municipality. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table 7: Aggregate-level results - Persistence

	(1) inc/ adult	(2) wage/ week	(3) wage/ hour	(4) hours/ earner	(5) earners/ job	(6) job/ adult
Big Storm						
current	-0.079***	-0.036**	-0.023**	-0.014	-0.029	-0.013**
	(0.026)	(0.015)	(0.011)	(0.010)	(0.025)	(0.006)
lag 1	-0.030	-0.017	-0.005	-0.011	-0.006	-0.007
	(0.026)	(0.015)	(0.014)	(0.011)	(0.027)	(0.006)
lag 2	0.036	0.017	-0.002	0.019*	0.026	-0.008
	(0.026)	(0.013)	(0.011)	(0.011)	(0.022)	(0.006)
lag 3	-0.036	-0.007	-0.007	-0.001	-0.012	-0.016**
	(0.022)	(0.012)	(0.013)	(0.011)	(0.022)	(0.007)
Small Storm (lags estimated but not displayed)						
current	-0.014	-0.014**	-0.013***	-0.001	0.001	-0.001
	(0.009)	(0.006)	(0.005)	(0.004)	(0.007)	(0.004)
Observations	20,579	20,579	20,579	20,579	20,602	20,835
R-squared	0.074	0.131	0.144	0.068	0.025	0.017

Notes: Results from weighted municipal*quarter regressions.The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). Regressions control for municipal fixed effects, time fixed effects as well as the share of the working age population in each education category, the share of women in the working age population, the number of men, the number of women, the number men age 15-30 and the number of women age 15-30. The sample is restricted to municipalities outside of Mindanao. The standard errors (in parentheses) account for potential correlation within province. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table 8: Individual-level results: A closer look at the private sector

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Decomposition of Impacts among Private Sector Wage Employment and Other Jobs						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	0.003	-0.022**	-0.017	0.018	-0.025**	0.008
	(0.016)	(0.010)	(0.012)	(0.012)	(0.010)	(0.006)
Small Storm	-0.016*	0.003	0.001	-0.015**	0.002	-0.001
	(0.009)	(0.005)	(0.006)	(0.007)	(0.006)	(0.003)
Big Storm * priv	-0.042**	0.052***	0.015	-0.055***	0.030**	-0.016**
	(0.021)	(0.016)	(0.014)	(0.017)	(0.012)	(0.007)
Small Storm * priv	0.022**	-0.026***	-0.004	0.024**	0.000	-0.004
	(0.011)	(0.009)	(0.007)	(0.009)	(0.006)	(0.003)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	660,650	1,430,357	660,650	669,711	660,650	660,650
R-squared	0.469	0.156	0.124	0.441	0.119	0.051
Panel B: Decomposition of Impacts among Permanent and Temporary Private Sector Wage Jobs						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm * permanent	-0.022*	0.005	0.004	-0.026**	0.006	-0.002
	(0.012)	(0.008)	(0.009)	(0.011)	(0.006)	(0.005)
Small Storm * permanent	-0.003	0.002	0.004	-0.007	0.004	-0.001
	(0.006)	(0.004)	(0.004)	(0.006)	(0.003)	(0.002)
Big Storm * temporary	-0.028	-0.042**	-0.038**	0.010	-0.027*	-0.012
	(0.020)	(0.018)	(0.018)	(0.017)	(0.014)	(0.009)
Small Storm * temporary	0.015	-0.009	-0.009	0.024***	-0.001	-0.009
	(0.010)	(0.009)	(0.009)	(0.009)	(0.007)	(0.006)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	465,245	510,571	465,245	465,245	465,245	465,245
R-squared	0.418	0.088	0.089	0.395	0.081	0.045
Equality F-stat	0.077	5.565	4.345	3.501	4.790	1.247
Equality p-val	0.782	0.019	0.037	0.062	0.029	0.264

Notes: Results from weighted individual regressions. In Panel A, the dependent variable is the log weekly wage for employed individuals (Column 1), number of hours worked for employed individuals (Column 2), number of hours worked for employed individuals earning a wage (Column 3), hourly wage for employed individuals (Column 4), number of days worked for employed individuals earning a wage (Column 5), number of hours worked per day for employed individuals earning a wage (Column 6). Regressions control for municipal fixed effects, time fixed effects as well as respondent's age, age square, education levels and gender. In Panel A regressions include a private sector dummy. In Panel B regressions include a permanent contract dummy. The standard errors (in parentheses) account for potential correlation within municipality. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table 9: Panel-level results: decomposition

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact on Earnings and Hours (All Employees)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.024**	-0.018**	-0.010	-0.019**	-0.004	-0.008*
	(0.010)	(0.009)	(0.008)	(0.008)	(0.006)	(0.004)
Small Storm	-0.007	-0.010**	-0.004	-0.005	0.000	-0.005**
	(0.006)	(0.005)	(0.004)	(0.005)	(0.004)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	267,038	699,704	277,932	267,038	277,928	277,928
R-squared	0.465	0.131	0.107	0.439	0.100	0.052
Panel B: Impact on Earnings and Hours (Same Job Type)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.015	-0.016*	0.006	-0.021**	0.001	0.005
	(0.012)	(0.009)	(0.009)	(0.010)	(0.007)	(0.004)
Small Storm	0.002	-0.008*	0.003	-0.002	0.002	0.000
	(0.007)	(0.005)	(0.005)	(0.006)	(0.004)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	194,717	502,444	195,728	194,717	195,726	195,726
R-squared	0.491	0.146	0.124	0.462	0.121	0.054
Mun Fe	No	No	No	No	No	No

Notes: Results from weighted individual regressions. In Panel A, the dependent variable is the log weekly wage for employed individuals (Column 1), number of hours worked for employed individuals (Column 2), number of hours worked for employed individuals earning a wage (Column 3), hourly wage for employed individuals (Column 4), number of days worked for employed individuals earning a wage (Column 5), number of hours worked per day for employed individuals earning a wage (Column 6). In Panel B, the dependent variables are a series of dummies equal to one if: the individual is employed (Column 1), the individual has a job (Column 2), the individual is employed but their wage is not observed (Column 3), the individual reports a wage regardless of employment status (Column 4), the individual reports having a job but working zero hours in the last 7 days (Column 5), the individual reports not having a job now, but having worked in the last 3 months (Column 6). Regressions control for time fixed effects as well as municipal fixed effects (Panel A) and individual fixed effects (Panel B). In Panel A, regression control for the respondent's age, age square, education levels and gender. The standard errors (in parentheses) account for potential correlation within municipality. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

For Online Publication

A.1 Theoretical Model

In this section we develop a model to explain our key findings for the private sector. We use a model with long-term contractual relationships, in which risk sharing occurs between workers and firms and workers are insured against shocks through work sharing.[24] While a model of spot markets for labour with perfectly inelastic labour supply might explain our results of lower wages and no changes in employment; we wish to explain the findings in the context of longer term contracts, which usually predict significant wage rigidities.

In the absence of downward rigidities, wage adjustments moderate the impact of shocks on firm labour demand and allow the market to clear. Our results show a fall in weekly wages across all private sector jobs. However, contracts must determine the trade-off between lay-offs and reductions in hours per worker, to the extent that total labour demand does fall during shocks. Similar models have been used to explain stylized facts from the United States, where labour markets are characterized by high variability of employment and relatively constant hours per worker (Burdett and Mortensen, 1980). Our setting is different, as hours appear to be relatively flexible.

We demonstrate conditions for which it is optimal for no lay-offs to occur. Workers are paid less and work fewer hours during periods when storms hit. The model predicts that wages and hours should fall, but we do not explicitly model the impact on the hourly wage. Where the adjustment occurs mostly through nominal wage adjustments, the hourly wage will fall significantly. This is the result we find for permanent jobs in the private sector. Where the adjustment in hours and total wages is similar, the effect on the hourly wage is ambiguous, which is what we find for temporary jobs in our data.

We use a version of the classic implicit contract models of Baily (1974) and Azariadis (1975). In the standard model, risk-averse firms and workers contract over total labour demand (employment) and wages for every state of the world. We adapt these models with extensions by Rosen (1985) and Miyazaki and Neary (1985), which focus on the role of lay-offs and hours per worker in optimal contracts by allowing hours per worker to enter the production function separately from the number of employed workers.

Rosen (1985) writes that implicit labour countries should specify 'precisely the amount of labour to be utilized and the wages to be paid in each state of nature, that is, conditional on information (random variables) observed by both parties.' Importantly, this assumption is realistic in our setting: storms are easily observable and can be contracted upon.

A The model

In the model, the realized state of the world θ represents a shock to firms' marginal revenue product, which enters firms' profit functions directly. We imagine that storms could impact firm profits by reducing output, for instance by destroying capital or disrupting the efficiency of labour inputs. Alternatively, storms could reduce domestic demand or regional trade, which would lead to lower prices. We do not distinguish between these channels; both are fully captured by changes in θ. Low realizations of θ correspond to large negative shocks, driven by typhoons in this paper. A representative firm contracts with a set of n workers. Workers and firms are risk averse. Contracts are perfectly enforceable and contingent on the realized state of the world θ. Therefore firms combine labour inputs through the function $f(.)$ with capital, prices and technology, all completely captured by θ, so that firm revenue is given by $\theta f(.)$.

In the benchmark model, firm production is a function of only a single labour input – usually the number of workers employed by the firm. If n is the number of workers under contract (which is constant in this model) and $p(\theta)$ is the proportion that is hired when the value of θ is realized, then production is given by $\theta f(pn)$. Labour demand is adjusted through changes in p alone for this simple case.

We adapt this benchmark model by allowing hours per worker h to be adjusted, so that firms use total worker-hours given by phn. Since labour is not necessarily perfectly divisible, production is given by $f(np, h)$. Firms pay wages only to workers they employ, at wage rate w. We simplify the standard model by assuming that firms cannot provide private insurance to laid-off workers, so workers only earn the outside wage when they are laid off.[25] Firm profit is given:

$$\pi = \theta f(pn, h) - wnp \tag{3}$$

Firms have utility over profits $v(\pi)$. This assumption is justified by credit and insurance market failures on the part of firms (Rosen, 1985; Blanchflower et al., 1996), which makes them unable to absorb short-term losses associated with the damage caused by storms.

Workers value consumption of wages w and leisure (the complement of hours worked h). So $U_h < 0$, $U_{hh} > 0$ while $U_w > 0$,$U_{ww} < 0$. If workers are laid off, they do not find alternative employment immediately; they earn only income from alternative work options, given here by $\overline{w}$.[26] In this setting, this alternative might correspond to going back to work in agriculture. A worker's expected utility, conditional on the realization of the state of the world, is given by:

$$EU(\theta) = pU(w, h) + (1 - p)U(\overline{w}, 0) \tag{4}$$

So firms offer contracts that specify wages, hours and the probability of employment for workers, $(w(\theta), h(\theta), p(\theta))$, for each realization of θ. For ease of exposition, we write each endogenous variable without specifying it as a function of θ, (w, h, p). Workers face the risk of being laid off with probability $(1 - p)$.

In this model firms compete for workers, driving up offers made to workers until firms push up against a probability constraint given by:

$$Ev(\pi) = \overline{v} \tag{5}$$

Thus the optimal contract problem is solved by the constrained maximisation of expected worker utility, $Eu(\theta)$, with Lagrange multipliers for (1) firms' profit constraints (λ) and (2) the total labour constraint $p \leq 1$ (η).[27] This second constraint is important: when it is binding at the optimal contract ($\eta > 0$), firms do not lay off workers.

This optimization problem yields the following first-order condition (FOC) for w, h and p, respectively:

$$U_1'(w, h) = \lambda v'(\pi)n \tag{6}$$

$$pU_2'(w, h) + \lambda v'(\pi)\theta f_2'(pn, h) = 0 \tag{7}$$

$$\eta = \lambda v'(\pi)[\theta n f_1'(pn, h) - wn] + U(w, h) - U(\overline{w}, 0) \tag{8}$$

Equation 6 expresses how wages react to economic shocks through risk sharing between workers and firms in a manner similar to the result in Blanchflower et al. (1996). When firms are very risk averse, workers accept large falls in wages in exchange for higher wages in normal periods. So the more risk averse firms are, the stronger the downward wage adjustment. However, firms could insure workers against lay-offs at the same time, especially if workers are particularly risk averse at low levels of consumption due to subsistence constraints. This would increase the sensitivity of wages to shocks, while employment levels remain constant. So workers accept a lower probability of unemployment in exchange for lower wages when shocks hit.[28]

Equation 6 shows an important insight: when firms are risk neutral ($v'(\pi) = 1$), wages respond to shocks to θ only if hours do, and if hours worked affects the marginal utility of consumption (non-separability) so that $U_{wh} \neq 0$. In this way, workers are paid less when they are working less because the marginal utility of consumption falls when they have more leisure time (when $U_{wh} > 0$). Our results show that for permanently employed workers in the private sector, hourly wages fall dramatically without commensurate reductions in the number of hours worked. This suggests that risk sharing is an important part of our results, since the magnitude of reductions in wages cannot be explained by substitutions between consumption and leisure alone.

1 Lay-offs and work sharing

Wage adjustments moderate the impact of shocks on labour demand. However, when labour demand falls, as it does in most of our empirical results, we seek to understand the relationship between changes in the number of hours worked and lay-offs. For ease of exposition, but without loss of generality, we put aside the issue of risk sharing from this point on. We assume that $v'(\pi) = 1$: firms are risk neutral. We focus instead on the "work-sharing" mechanisms that determine the trade-off between hours per worker and employment.[29]

The second and third FOCs capture the trade-off between the number of hours worked and lay-offs. Recall that $U_2'(w,h) < 0$. We re-arrange Equation 7 and substitute λ from Equation 6:

$$\begin{aligned} \theta f_2'(pn,h) &= -\frac{pU_2'(w,h)}{\lambda} \\ \theta f_2'(pn,h) &= -\frac{npU_2'(w,h)}{U_1'(w,h)} \end{aligned} \tag{9}$$

Do firms adjust down the hours worked per worker h (work sharing) or reduce employment p (lay-offs) in response to bad realizations of θ? This is determined by the value of η for the optimal contract. Miyazaki and Neary (1985) show that a precondition for lay-offs is that $\eta < 0$ when $p = 1$. After all, if the optimal outcome is full employment ($p^* = 1$), then $\eta > 0$. But if lay-offs occur, the optimal value for p^* lies on $0 < p < 1$ and $\eta = 0$. This implies that at $p = 1$, then $\eta < 0$. In other words, if firms were 'forced' to maintain full employment when the optimal solution has $p < 1$, the marginal product of additional employment would be less than the marginal costs (the wage bill and the foregone leisure of those workers), and firms would wish to make lay-offs.

The expression for 8 is surprisingly tractable. First we rearrange, and add and subtract, terms:

$$\begin{aligned}\eta &= \lambda n[\theta f_1'(pn,h) - \frac{h\theta f_2'(pn,h)}{pn} - \overline{w}] \\ &\quad + U(w,h) - U(\overline{w},0) - (w-\overline{w})\lambda n + \frac{\lambda h\theta f_2'(pn,h)}{p}\end{aligned} \tag{10}$$

Then substituting from 9 and 6:

$$\begin{aligned}\eta &= \lambda n[\theta f_1'(pn,h) - \frac{h\theta f_2'(pn,h)}{pn} - \overline{w}] \\ &\quad + U(w,h) - U(\overline{w},0) - (w-\overline{w})U_1'(w,h) - hU_2'(w,h)\end{aligned} \tag{11}$$

$$\eta = \lambda n[\theta f_1'(pn,h) - \frac{h\theta f_2'(pn,h)}{pn} - \overline{w}] + H(w,h) \tag{12}$$

In the second part of 11, we denote that $H(w,h)$, which is strictly positive, by the concavity of U.

Lay-offs occur when $\eta < 0$ at $p = 1$: when expression 12 is negative. Thus a necessary, but not sufficient, condition for lay-offs is:

$$n[\theta f_1'(n,h) - \overline{w}] < h\theta f_2'(n,h) \tag{13}$$

The LHS of expression 13 shows the marginal product of employment at the extensive margin, and the RHS shows the marginal product of employment at the intensive margin. If the latter is larger than the former, firms would prefer to lay off workers and increase hours.

So lay-offs are more likely when $\overline{w}$ is larger: workers have better outside options and thus are more tolerant of lay-offs. This result is similar to Baily (1977), who argues that unemployment insurance can encourage lay-offs. Similarly, when workers are less risk averse, so that $H(w, h)$ is smaller, lay-offs are more likely to occur.

If workers have no alternative earnings options, the expression reduces to $n\theta f_1'(pn, h) < h\theta f_2'(pn, h)$. So lay-offs occur only if the marginal product of increased hours is large enough relative to the marginal product of additional labour at the full employment level ($p = 1$).

2 Divisibility of labour

In the limit case in which labour is perfectly divisible, firms' production becomes $f(pn, h) = f(pnh)$. Hours per worker and additional workers are perfect substitutes. This production function with divisible labour is used in Stiglitz (1986). In this case $f_1'(pn, h) = f'(.)h$, and $f_2'(pn, h) = f'(.)pn$. Therefore $h\theta f_2'(pn, h) = n\theta f_1'(pn, h)$, so these terms cancel each other out and η becomes, at $p = 1$:

$$\begin{aligned}\eta &= -\lambda n\overline{w} + H(w, h) \\ &= U(w, h) - U(\overline{w}, 0) - (w)U_1'(w, h) + hU_2'(w, h) \qquad (14)\end{aligned}$$

Firms lay workers off depending on the opportunity cost of employment: the outside wage. Notice that if $\overline{w} = 0$, lay-offs never occur.[30] This logic explains why the case for lay-offs depends on the divisibility of labour. Following Rosen (1985), production is written as:

$$f(np, h) = f(np\gamma(h)) \qquad (15)$$

where $\gamma(h)$ is often assumed to be ogive shaped: at low numbers of hours per worker, returns on hours are small due to the fixed costs of worker days. This could be the case if the first few hours of the workday are dedicated to setting up or preparation before productive activities start. Then returns would increase rapidly for intermediate values of h and then begin to suffer diminishing marginal returns as workers fatigue during the course of the day.

With this production function, the first-order condition for p becomes:

$$\eta = \lambda n[\theta f'(.)\gamma(h) - h\theta f'(.)\gamma'(h) - \overline{w}] + H(w, h) \qquad (16)$$

Again with $\overline{w} = 0$, lay-offs happen only if:

$$\gamma(h)/h < \gamma'(h) \tag{17}$$

This says, of course, that when the marginal returns on hours worked are higher than the average returns on hours worked, firms prefer to keep hours constant at a high level and employ fewer (more) workers in response to bad (good) realizations of θ. Given the assumption of the ogive shape of γ, there are many points along $\gamma(h)$ at which this holds. However, beyond a certain point, diminishing marginal returns mean that firms prefer to cut workers' hours rather than lay them off.

The impact of storms on hours is about 3.5 per cent. If average hours are about 48 in a 'normal' period (where $p = 1$), they fall to only about 46.4 hours when shocks hit. Very specific conditions on the slope of γ would have to prevail to result in a switch of sign of $\gamma(h)/h - \gamma'(h)$ on the range 46.4-48.0. The second FOC in hours (Equation 9) with this production function becomes:

$$\theta f'(.)\gamma'(h) = \frac{U_2'(w,h)}{U_1'(w,h)} \tag{18}$$

The optimal outcome for h need not be close to an inflection point where $\gamma(h)/h = \gamma'(h)$. Indeed, if decreasing returns on hours per worker take a long time to kick in, implying that labour is divisible for reasonably high levels of h, then firms will prefer to reduce hours rather than lay off workers.

Recall that we are talking about a necessary but not sufficient condition for lay-offs. With low $\overline{w}$, $H(w, h)$ get very large, which makes lay-offs less likely, even when labour is relatively indivisible.

B Discussion

The aim of this framework is not to argue that lay-offs do or do not occur in optimal contract models. Indeed, without strong assumptions on the functional forms of $U(w, h)$ and $f(np, h)$, these models can say little more than $dp/d\theta \geq 0$ and $dh/d\theta \geq 0$ (Rosen, 1985). Instead we have made a case for work sharing as a way of insuring workers against risk (especially when severance pay is not made). The results presented here suggest that there are parameter values under which adjustments in hours can dominate adjustments in employment.

Second, we have shown that three key factors determine trade-offs between work sharing (reduction in hours) and lay-offs. Firms are more likely to reduce hours and maintain full employment if 1) workers are more risk averse, 2) workers' outside options are worse and 3) labour is relatively divisible. These findings are similar to those in Azariadis (1975).

Our empirical results show large adjustments in wages and hours, and few lay-offs. We argue that these findings are not surprising in light of the model: workers may well be very risk averse when their entire livelihoods are based on their wage earnings, and outside options may be made considerably worse when storms hit, because of the damage caused to home production and own-farm agriculture. We have no direct evidence on the divisibility of labour, but argue that our results suggest that firms are relatively willing to reduce workers' hours.

This illuminates an important point. It may be the case that labour is highly indivisible, but that workers' high risk aversion means that firms are cutting hours and wages to protect workers from lay-offs. This would imply inefficient levels of hours compared to a situation in which workers are fully insured and firms can adjust optimally by reducing the size of their labour force but keeping hours high. This again mirrors the argument in Rosen (1985). Markets for either private or public insurance for workers would considerably improve the efficiency of outcomes after storms hit.

The model also illuminates the role of labour supply. The extent of flexibility of hours is in part due to workers' preference for leisure time (or time off work for home production). In our setting we have argued that workers may have a particularly strong preference for more time off work when storms hit, in order to spend time repairing damage caused by storms.

However, workers' outside options are still poor, and may be particularly poor after storms hit because of storm destruction of farming or other consumption-generating activities at home. This limits labour supply elasticity at the extensive margin. In this way, workers are willing to sacrifice hours at the intensive margin (and therefore wages), as governed by the relationship given in Equation 6, in order to avoid being laid off. We have no direct evidence of this phenomenon of increased labour supply elasticity during storms, but this mechanism is consistent with the results of Jayachandran (2006).

This paper has not considered dynamic considerations that could be contributing to our finding of no lay-offs. That is, we have not assumed that firms have a preference to 'hoard' labour, which would be the case if there were adjustment costs associated with hiring or firing labour (Bloom, 2009), or if there were job-specific returns on human capital (Hashimoto, 1981). Adding these elements to the model would strengthen our results by making firms less willing to lay off workers.

A.2 Background on the Typhoon data

We explain the wind-speed model used in this paper in more detail, and the different parameter choices involved. Our windspeed model comes from Holland (1980). It is parameterized by a wind-decay smoothing parameter ('b') , and a radius parameter, which determines the distance at which wind-speed is at its peak ('rmax'). These parameter choices generate windspeed profiles, as a function of the distance from the eye of the storm, and the pressure of the eye of the storm. The choices of these parameter can differ across contexts, we estimate our results for a number of different parameter choices within the theoretically plausible range.[31] The specific functional form is given by:

$$V_{ds} = [(b/\rho)(rmax/d)^b(p_a - p_s)exp(-((rmax/d)^b)) + (d^2f^2)/4]^{1/2} - (df)/2$$

where V_{ds} is the windspeed experienced from storm s, at a point with distance d from the path of the storm. p_s the pressure of the eye of the storm at that point when it passed closest to that point. p_a gives the ambient pressure, chosen here to reflect the climate in the North Pacific. f is the Coriolis parameter, and ρ is the density of air, both constants. Finally, b is the smoothing parameter, and $rmax$ the radius parameter. As shown by Holland (1980), the radius of maximum windspeed can be approximated, under simplifying assumptions, by $rmax^{1/b}$, and the maximum windspeed at that point by $(b/\rho e)^{1/2}$.

For our main results we estimate the effects of storms modelled with a wind-decay smoothing parameter ('b') equal to 2.2, and a radius parameter ('rmax') equal to 25km. We selected this parameter choice because it mostly closely matches publicly available data on the largest super storms to make landfall on the Philippines during this period. In Table A.54 we reality check our storm data against records of the storm impacts in the Philippines. For each of the Category 4--5 storms that made windfall during our study period, we look at how many municipalities were registered as being effected by a storm that large for different parameterizations in our data. We show that our chosen paramaterization performs optimally, predicting 14 of the 15 largest storms to make windfall.[32] In total, we register 39 storms that show up as Typhoons over the period of our, 14 of which we classify as very big storms. The average Typhoon that hits the country registered as a Typhoon (Category 1-3 storm) in 78 municipalities, while the average Super Typhoon registered as a Super Typhoon in 42 municipailities, and as a Typhoon in 130 municipalities.

We show that our main findings are robust to alternative parameter choices, on either side of our chosen specification, symmetrically. In addition, our results are robust, and very similar, for the parameterization used in an early draft of this paper, namely wind-decay smoothing parameter ('b') equal to 1.8, and a radius parameter ('rmax') equal to 20km. This is outside of the range reported in the main part of the paper, but the results are replicated in the Online Appendix. Parameterizations with $b < 1.8$ or $rmax < 20$ perform relatively badly, as they tend to under-predict a number of large storms that hit the country in this period.

A.3 Background on the Labor Force Survey

Note: The information below is taken from the LFS Enumerator Manual.

A Key terms

Labor Force. It refers to the population 15 years old and over who contribute to the production of goods and services in the country. It comprises the employed and unemployed.

Employed. It consists of persons in the labor force who are reported either as at work or with a job or business although not at work. Persons at work are those who did some work, even for an hour during the reference period.

Unemployed. It consists of persons in the labor force who are reported as (1) without work; and (2) currently available for work; and (3) seeking work or not seeking work because of the belief that no work is available, or awaiting results of previous job application, or because of temporary illness or disability, bad weather or waiting for rehire or job recall.

Reference period. It correspondent to the seven days preceding the date of visit of the interviewer or enumerator.

B Questionnaire

This section describes the way information on employment, hours of work and earnings are collected. The full questionnaire is available below.

1 Employment

For each household member above the age 15, the enumerators ask the following question: *Did (NAME) do any work for at leat one hour during the past week?*

"Worked at all" for purposes of this survey, means that a person reported to his place of work and performed his duties/activities for at least one hour during the reference week. One hour is the minimum time a person should be engaged in an economic activity to be considered as employed.

This refers not only to the work done in the primary job but refers also to the work done in other jobs (secondary job). Hence, if he did not work in his primary job during the past week but rather worked in his secondary job, he should have an answer of ?Yes? in this column.

2 Hours worked

The respondent is also asked about the *total number of hours worked during the past week.*

Total hours worked at a particular job refers to (1) hours actually worked during normal periods of work; (2) over-time; (3) time spent at the place of work on activities such as the preparation of the workplace, repairs and maintenance, the preparation and cleaning of tools, and the preparation of receipts, time sheets and reports; (4) time spent at the place of work waiting or standing-by for customers or for such reasons as lack of supply of work, breakdown of machinery, or accidents, or time spent at the place of work during which no work is done but for which payment is made under a guaranteed employment contract; and (5) time corresponding to short rest periods at the workplace, including tea and coffee breaks.

Total hours worked exclude (1) hours paid for but not worked, such as paid vacation leave, paid public holidays, or paid sick leave; (2) meal breaks; and (3) time spent on travel from home to work and vice versa.

Total hours worked should in principle be confined to hours spent on economic activities. In practice, however, this distinction may be difficult for certain categories of workers. For example, in family farms agricultural activities are often intermingled with domestic chores, not only because agricultural activities and domestic chores are performed simultaneously, but also because the two types of activities are close in nature.

Similar problems may arise in connection with home-based workers and workers in household enterprises, as well as with apprentices and trainees, whose activities may combine elements of learning with productive work, performed at the same place and during the same reference period.

3 Earnings

The respondent is also asked about the *basic pay per day (in cash).*

Basic pay is the pay for normal time, prior to deductions of social security contributions, withholding taxes, etc. It excludes allowances, bonuses, commissions, overtime pay, benefits in kind, etc. Also called basic wage. If a worker receives only in kind salaries and wages as payment for their services (not additional benefits), it should be imputed and entered as basic pay.

Entries for this column must be salaries/wages per day.

Per piece: Rate per piece*Number of pieces per day

Per Hour: Rate Per Hour* Normal working Hours (excluding OT)

The Normal Working Hours to be used in the computation of salaries and wages must not include OT services. This should be differentiated from the normal working hours, which may possibly include working hours for OT services.

4 Job Classifications

In the paper we structure the analysis by looking at workers in different categories of employment. These are defined as follows: PERMANENT PRIVATE SECTOR WAGE EMPLOYMENT: These are jobs that the respondent considers permanent. Wages are usually paid on a monthly basis; daily wages are also common. These jobs are most likely to be based on longer-term relationships and contracts, and are the focus of much of the analysis of the paper.

TEMPORARY PRIVATE SECTOR WAGE EMPLOYMENT: These are jobs at private establishments that the workers identified as short term. This includes casual labour, seasonal work and short-term contracts. The most common mode of payment is a daily wage, although piece-rate and *pakyaw* payments are more common than for permanent jobs.[33]

GOVERNMENT WORK: Formal wage work in the public sector, usually paid monthly. Most of these jobs are permanent.

OWN FARM: If these jobs are paid (which they rarely are) they are paid on a daily, commission or *pakyaw* basis.This work is mostly subsistence agriculture classified as self-employment or unpaid family work. Wages are rarely observed for these jobs, and so these workers do not influence the estimates on aggregate wages.

WAGE FARM: This is wage employment on a farm other the household's own. These jobs are usually paid on a daily basis.

SELF EMPLOYMENT: These are mostly very small retail or small-scale construction enterprises. This category excludes those who define themselves as self-employed agriculturists. Wages were rarely observed for this category. These workers also do not influence our analysis of aggregate wages.

C Sampling

The section below is taken from the Philippine Statistics Authority data archive.

1 Sampling Procedure

he sampling design of the Labor Force Survey (LFS) uses the sampling design of the 2003 Master Sample (MS) for Household Surveys that started July 2003.

Sampling Frame. As in most household surveys, the 2003 MS used an area sample design. The Enumeration Area Reference File (EARF) of the 2000 Census of Population and Housing (CPH) was utilized as sampling frame. The EARF contains the number of households by enumeration area (EA) in each barangay. This frame was used to form the primary sampling units (PSUs). With consideration of the period for which the 2003 MS will be in use, the PSUs were formed/defined as a barangay or a combination of barangays with at least 500 households.

Stratification Scheme. Startification involves the division of the entire population into non-overlapping subgroups called starta. Prior to sample selection, the PSUs in each domain were stratified as follows:

1. All large PSUs were treated as separate strata and were referred to as certainty selections (self-representing PSUs). A PSU was considered large if it has a large probability of selection.

2. All other PSUs were then stratified by province, highly urbanized city (HUC) and independent component city (ICC).

3. Within each province/HUC/ICC, the PSUs were further stratified or grouped with respect to some socio-economic variables that were related to poverty incidence. These variables were: (a) the proportion of strongly built houses (PSTRONG); (b) an indication of the proportion of households engaged in agriculture (AGRI); and (c) the per-capita income (PERCAPITA).

Sample Selection. To have some control over the subsample size, the PSUs were selected with probability proportional to some estimated measure of size. The size measure refers to the total number of households from the 2000 CPH. Because of the wide variation in PSU sizes, PSUs with selection probabilities greater than 1 were identified and were included in the sample as certainty selections.

At the second stage, enumeration areas (EAs) were selected within sampled PSUs, and at the third stage, housing units were selected within sampled EAs. Generally, all households in sampled housing units were enumerated, except for few cases when the number of households in a housing unit exceeds three. In which case, a sample of three households in a sampled housing unit was selected at random with equal probability.

An EA is defined as an area with discernable boundaries within barangays, consisting of about 150 contiguous households. These EAs were identified during the 2000 CPH. A housing unit is a structurally separate and independent place of abode which, by the way it has been constructed, converted, or arranged, is intended for habitation by a household

Sample Size. The 2003 Master Sample consist of a sample of 2,835 PSUs of which 330 were certainty PSUs and 2,505 were non certainty PSUs. The number of households for the 2000 CPH was used as measure of size. The entire MS was divided into four sub-samples or independent replicates, such as a quarter sample contains one fourth of the PSUs found in one replicate; a half-sample contains one-half of the PSUs in two replicates. Thus, the survey covers a nationwide sample of about 51,000 households deemed sufficient to measure the levels of employment and unemployment at the national and regional levels.

Strategy for non-response. Replacement of sample households within the sample housing units is allowed only if the listed sample households had moved out of the housing unit. Replacement should be the household currently residing in the sample housing unit previously occupied by the original sample.

2 Weighting

Calculation of Basic Weights: Following a standard approach, the weights to be used in analyzing surveys based on the 2003 MS are developed in three stages. First, base weights are computed to compensate for the unequal selection probabilities in the sample design. Second, the base weights are adjusted to compensate for unit non-response. Third , the non-response adjusted weights are further adjusted to make some weighted sample distributions to conform to some known population totals.

Final Survey Weight: The final survey weight assigned to each responding unit is computed as the product of the base weight, the non-response adjustment, and the population weighting adjustment. The final weights should be used in all analyses to produce valid estimates of population parameters.

D Survey Implementation

Enumerators. The number enumerators is about 700 including regular employees of the office for regular LFS meaning there are no rider survey.

Data Collection. The enumeration starts on the 8th day of the first month of the quarter until the end of the month. The enumeration period usually about 18 to 21 days.

Adjustment for natural disasters. In case of floods or typhoons, enumerators are advised to go to the area once the flood subsides/after the typhoon passes. If the enumerators are unable to go during the enumeration period then those observations are considered as non-response. According to the PSA, the number of non-response due to flood or typhoon is very minimal as individuals are only away temporarily (if at all).

INTEGRATED SURVEY OF HOUSEHOLDS
ISH FORM 2

NSCB APPROVAL NO. NSO – 0516 – 01
Expires 31 December 31, 2008

REPUBLIC OF THE PHILIPPINES
NATIONAL STATISTICS OFFICE
MANILA

Confidentiality:

This survey is authorized by Commonwealth Act No. 591. All data obtained cannot be used for taxation, investigation or law enforcement purposes.

LABOR FORCE SURVEY

Sir/Madam:

The National Statistics Office in cooperation with the Department of Labor and Employment is undertaking a Labor Force Survey for the purpose of gathering data on the economic activities of the households in the Philippines. Data on labor force and its characteristics will be collected.

Your household is one of the 51,000 sample households selected nationwide. With your cooperation, this survey will yield accurate and up-to-date data needed for effective planning and policy-decision making.

Please be assured that the data you supply us will be held STRICTLY CONFIDENTIAL and your report cannot be used for purposes of taxation, investigation or enforcement procedure, nor will it be published except in the form of statistical summaries in which no reference to any individual person shall appear.

Your cooperation is earnestly solicited.

Very truly yours,

CARMELITA N. ERICTA
Administrator
National Statistics Office
P.O Box 779, Manila

Identification and Other Information

Set ____ of ____ sets

Geographic Identification Codes

Province ______________________________

Mun/City ______________________________

Bgy ______________________________

EA ………………………………………………

SHSN ……………………………………………

HCN ……………………………………………

Design Code

Replicate ……………………………………………………..

Stratum ……………………………………..

PSU No. ……………………………………

Rotation Group ……………………………………………

Number of Households in the housing unit ………………..

Certification

I hereby certify that the data gathered in this questionnaire were obtained/reviewed by me personally and in accordance with instructions.

______________________________ ______________
Signature over Printed Name of Enumerator Date Accomplished

______________________________ ______________
Signature over Printed Name of Supervisor Date Reviewed

Name of Respondent: Line No.

____

Name of Household Head:

____

Address:

____

Interview Status *(Encircle appropriate code and enter in the box provided)*

1 Completed Interview
2 Refusal
3 Temporarily away/ Not at home/ On vacation
4 Vacant housing Unit
5 Housing unit demolished, destroyed by fire, typhoon, etc.
6 Others, specify ____________
7 Critical area, flooded area

Household Auxiliary Information *(Encircle appropriate code and enter in the box provided)*

1 Household same as in previous quarter, go to question A

2 New occupant of old sampled housing unit, proceed with interview

3 Rotated household, proceed with interview

A. Is/Are there any household member/s who moved out of the household?
1 Yes 2 No, go to B

If Yes, how many? (Enter the number in the box provided)

Death
Marriage
Job
Studies
Others, specify ____________________

B. Is/Are there any new member/s of this household?
1 Yes 2 No
Proceed with interview

RTO1

A. DEMOGRAPHIC CHARACTERISTICS												B. ECONOMIC			
All Persons								5 Years Old & Over		5-24 YearsOld	15 Years Old & Over	1. For persons For persons 5 Years Old and Over			
Line No. En-cir-cle res-pon-dent	Household member as of date of visit (Last name, first name)	Is ___ a new mem-ber of this house hold? 1 YES 2 NO Skip to Col. 5	What was ___'s line num-ber in the pre-vious quart-er?	Rela-tion-ship to HH head (En-ter code)	Sex 1 M 2 F (En-ter code)	Age as of last birth-day (Check col. 7A for members 5 years old and over)		Mari-tal (ci-vil) sta-tus (En-ter code)	Highest grade com-pleted (Enter code/ specify degree	Is ______ currently attending school? 1 YES 2 NO	Overseas Filipino Indicator (Enter Code) If code is 1,2 or 3 go to next HH member	Did _____ do any work for at least one hour during the past week? 1 YES, skip to Col. 14 2 NO	Although ____ did not work, did ____ have a job or business during the past week? 1 YES 2 NO, skip to Col. 31	What was _________'s primary occupation during the past week? (Specify, occupation e.g. elementary teacher, palay farmer, etc.)	Do not fill
(1)	(2)	(3)	(4)	(5)	(6)	(7)	7A)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
01				01											
02															
03															
04															
05															
06															
07															
08															
09															
10															
11															
12															
13															
14															
15															

Codes for Col. 5 - Relationship
01 - Head
02 - Wife/Spouse
03 - Son/daughter
04 - Brother/sister
05 - Son-in-law/daughter-in-law
06 - Grandson/granddaughter
07 - Father/Mother
08 - Other Relative
09 - Boarder
10 - Domestic helper
11 - Non-relative

Codes for Col. 8 - Marital Status
1 - Single
2 - Married
3 - Widowed
4 - Divorced/Separated
5 - Unknown

Codes for Col.11 - Overseas Filipino Indicator
1 - OCW
2 -Workers other than OCW
3 - Employees in Phil. Embassy, Consulates & other missions
4 - Students abroad/tourists
5 - Others

Codes for Col 9 - Highest Grade Completed
00 - No grade completed
01 - Elementary Undergraduate
02 - Elementary Graduate
03 - High School Undergraduate
04 - High School Graduate
05 - College Undergraduate

For College Graduate

Specify the bachelor's or higher degree completed and field of study

C H A R A C T E R I S T I C S

who ever worked or had a job/business during the past week

For persons 5 Years Old and Over		F O R P E R S O N S 1 5 Y E A R S O L D A N D O V E R														
Kind of business/ industry (Specify industry e.g. public school, palay farm, etc.)	Do not fill	(Check col. for mem-bers 15 years old and over	Na-ture of Em-ploy-ment (Enter code)	Normal working hours per day during the past week	Total number of hours worked during the past week	Did___ want more hours of work during the past week? 1 YES 2 NO	Did ___ look for addi-tional work during the past week? 1 YES 2 NO	Was this ___'s first time to do any work? 1 YES 2 NO	Class of worker (Enter Code) Go to Col. 27 if code is 3,4 or 6	For members with code 0,1,2 or 5 in Col. 24 (Class of worker) Basis of Pay-ment Enter Code	Basic Pay per Day In Cash	Did ____ have other job or business during the past week? 1 YES 2 NO, Skip to Col. 29	How many other job/s did ____ have during the past week?	Total hours worked for all jobs during the past week Skip to Col. 42 if 48 hrs or less	Reasons for working more than 48 hours during the past week (Enter code) Skip to Col. 42	L I n e No.
(16)	(17)		(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(1)
																01
																02
																03
																04
																05
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																11
																12
																13
																14
																15

Codes for Col.18-
Nature of Employment
1 - Permanent job/business/ unpaid family work
2 - Short-term or seasonal or casual job/business/unpaid family work
3 - Worked for different employer on day to day or week to week basis

Codes for Col. 24 - Class of Worker
0 - Worked for private household
1 - Worked for private establishment
2 - Worked for gov't/gov't corporation
3 - Self-employed without any paid employee
4 - Employer in own family-operated farm or business
5 - Worked with pay on own family-operated farm or business
6 - Worked without pay on own family-operated farm or business

Codes for Col. 25 - Basis of Payment
0 - In kind, imputed (received as wage/salary)
1 - Per piece
2 - Per hour
3 - Per day
4 - Monthly
5 - Pakyaw
6 - Other salaries/wages (Specify)
7 - Not salaries/wages (specify, e.g. commission basis)

Codes for Col. 30
Reasons for long hours of work
1 - Wanted more earnings
2 - Requirements of the job
3 - Exceptional week
4 - Ambition, passion for job
5 - Other reasons (specify)

Line No.	Col. No.	Others, Specify

Computation for Basic Pay

RTO2

Line No.	E C O N O M I C C H A R A C T E R I S T I C S (15 YEARS OLD AND OVER)													
	2. For persons who did not work and had no job/business during the past week										Activity during the past quarter			
	Did ____ look for work or try to establish a business during the past week? 1 YES 2 NO, Skip to Col. 35	Was this _____'s first time to look for work or try to establish a business? 1 YES 2 NO	What has _____ been doing to find work? (Enter code)	How many weeks has ____ been looking for work? Skip to Col. 37	Why did _____ not look for work? (Enter code)	When was the last time _____ looked for work? (Enter code)	Had opportunity for work existed last week or within two weeks, would ____have been available? 1 YES 2 N0	Is ___ willing to take up work during the past week or within 2 weeks? 1 YES 2 NO	Did ___ work at anytime before 1 YES 2 NO, Go to next hh member	What was ____ last occupation? (Specify, occupation e.g. elementary teacher, palay farmer, etc.) Skip to Col. 42	Do not fill	Did _____ work at all or had a job or business during the past quarter? 1 YES 2 NO, Go to next hh member	Kind of business/ industry (Specify industry e.g. public school, palay farm, etc.) Go to next hh member	Do not fill
(1)	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)	(41)	(42)	(43)	(44)
01														
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12														
13														
14														
15														

Codes for Col. 33
Job Search Method
1 - Registered in public employment agency
2 - Registered in private employment agency
3 - Approached employer directly
4 - Approached relatives or friends
5 - Placed or answered advertisements
6 - Other, specify

Codes for Col. 35
Reasons not looking for work
1 - Tired/believe no work available
2 - Awaiting results of previous job application
→ GO TO COL. 36
3 - Temporary illness/disability
4 - Bad weather
5 - Waiting for rehire/job recall
→ GO TO COL. 37
6 - Too young/old or retired/permanent disability
7 - Household, family duties
8 - Schooling
9 - Others, specify
→ GO TO COL. 39

Codes for Col. 36
Last time to look for work
1 - Within last month
2 - One to six months ago
3 - More than six months ago

Line No.	Col. No.	Others, Specify

Remarks

A.4 Additional Results

A Further robustness checks

As discussed in Section 2, our preferred storm measure uses a smoothing parameter of $b = 2$ and a wind-speed radius of $r = 25$. We generate alternative storm measures, using the same wind-speed model, but with different parameters for the wind-speed decay function and the radius of the storm, symmetrically on either side of our main parameterization. In Table A.21 we estimate the impact on earnings and employment, using our preferred specification (Column 4 in Table 3) but with the alternative storm measures.[34] We find broadly similar results across a variety of different wind-speed models: the impact on total wages is always large and significant while impacts on employment are small and marginally significant. In Appendix (Tables A.3-A.11) we replicate the decomposition results in Table 4, for each different storm parameterization, and show that the findings are similar here too. We find that in all cases, different parameterizations support our story of falling wages without impacts on employment, and declines in hourly wages. And some, but not all, specifications the effect on hours per worked is significantly negative.

In Table A.2 we show that the main employment and aggregate results are robust to different storm model parameterizations, on either side of our chosen parameter choice. Further, in Tables A.12 to A.20, we show that the decomposition results are similar across the 9 different permutations of parameter choices. The impact on hourly wages shows up the most significant driver of changes in wages, although the impact on hours worked is always large, and often statistically significant. Again, these results are robust to iteratively dropping the entire period in which each large storm hit, to show that the results are not driven by any one particular storm (Table A.22).

Are our results driven by just one or two large storms? There are ten storms during our study period that we classify as big SS scale at the time that made windfall, in at least one Philippine municipality. Given the relatively small number of storms, we check whether our results are driven by just one or two large storms, by re-estimating our results, dropping in turn the months in which each of these large storms made landfall. We show that the main results in Table 3 (shown in a new table in the main paper) and the decompositions in Table 4 (shown in 10 different tables in the appendix), are not significantly changed by dropping any one of the large storms.

The results are robust to using alternative measures of storm strength (Tables A.23 and A.24) before we parameterize them according to the Saffir-Simpson scale. However, we find that only the largest storms (in terms of windspeed) have impacts on the labour market.

Finally, we check that the results are driven by the very large storms, and not by other storm charactersitics that are correlated with windspeeds. We show that the results are not driven by wide storms that hit many municipalities at once, regardless of their windspeed. We show that there is no significant difference between storms that move slowly over the islands, versus those that moved quickly, and we find no evidence that plaes that were hit more often, during the duration of our study, suffered more from the large storms. These results are presented in Tables A.27, A.25, and A.26 respectively, in the Online Appendix.

B Heterogeneity

We now explore heterogeneity in the estimated effects. We focus on two main dimensions: the level of urbanisation and the type of occupation. The evidence suggests that urban and rural areas are equally affected by strong storms. We further establish that managers tend to increase their earnings during storms due to an increase in the number of hours worked.

1 Urban–rural heterogeneity

The extent of wage flexibility might differ between rural and urban areas. In rural settings, we might expect that outside options might be more sensitive to storms: labour markets are likely to be thinner (so workers are less likely to find alternative work in other jobs), and rural households rely far more on subsistence agriculture to supplement incomes and insure against the risk of being laid off. Subsistence agriculture is very likely to be adversely effected by storms, which might limit lower-paid workers' outside options and labour supply flexibility, and lead to stronger downward adjustment of wages (Jayachandran, 2006). Therefore wages in labour contracts might be more likely to adjust downwards during shocks. By contrast, it may be that smaller communities and more traditional behavioural norms in rural areas regulate labour markets and ensure that wages cannot fall due after shocks (Kaur, 2014).

We estimate Equation (2) but interact the storms variables with a city dummy (Table A.36). We find no significant heterogeneity between the rural and urban areas.[35] All of the effect comes through the storm variable; the interaction term is not significant.[36]

One additional important result emerges. Until now we have seen little impact of small storms on labour outcomes. This is perhaps because the damage caused by these storms, while often severe for small-scale farmers and individual households, is not enough to significantly disrupt the formal sector. However, Table A.36 suggests that for rural areas, small storms do have an impact. The size of the effect is small relative to larger storms, but statistically significant. By contrast, the sign on the interaction of *small storm* and *city* in Column 1 is significant, in the opposite direction, suggesting that the impact of being hit by a small storm is completely mitigated in urban areas.

2 Skill bias

A long literature looks at the impacts of large shocks on the relative composition and earnings within local labour markets (Moretti, 2010). Kirchberger (2014) shows that damage caused by earthquakes leads to persistent increases in wage premia in the construction sector when reconstruction occurs. Keane and Prasad (1996) show that large spikes in the price of oil lead to a rise in the relative wage of more skilled workers, although wages decline for workers overall.

We estimate Equation (2) on the sample of private sector workers and distinguish between individuals employed as managers and individuals employed in other occupations (Table A.37). The negative coefficient on average wages for non-manager workers estimated here is consistent with the main results. However, we find that managers see large rises in their wages, which is significantly different from the impact on non-managers. Interestingly, this effect is not driven by an increase in the hourly wages of these workers (although the coefficient is positive, it is not significant). The increase in managers' wages is driven by large increases in the number of hours they work (they work both longer days and more days). We speculate that these results are driven by the need for managerial oversight during times of crisis, as firms shift priorities away from usual business to recovering assets, dealing with storm damage and otherwise adjusting to shocks. Firms may arrange with managers to work additional (or overtime) hours during times of crisis to manage the fallout from storms.

C Comparing aggregate and individual results

We note discrepancies between the aggregate and individual data in the effects estimated thus far. The total effect on total wages per person at the municipal level is 6.7 per cent (using the log of total wages). This effect represents our estimate of the total average percentage change in labour earnings due to storms. It includes the effects of storms on average wages, employment and missing incomes. By comparison, the estimated effect on average observed wages in the aggregate data is 3.6 per cent, while the estimated effect on average wages in the individual data is 2.1 per cent. This discrepancy seems to be driven by the use of the log of aggregate wages. If poorer municipalities are hit harder by storms (in relative terms) then the impact on the log of the average wage will be different from the average impact on the log of individual wages. We fully reconcile these results by looking at the impact of storms on the main variables in *levels*, in the Online Appendix, Table A.38. This also allows us to examine the impact of the storms on income per adult for the individual data. In this table we find that the results are almost identical between the two datasets. When expressed as the percentage of the mean dependent variable, we find that storms have a 3 per cent impact on income per adult. This shows that the results are driven by the use of logarithms of aggregate data rather than inconsistencies in our application of sample weights or definitions of variables.

Table A.1: Replication of Main Aggregate Results (Income and Employment) with Alternative Storm Paramaterizations

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Smoothing paramater b = 2.4						
Radius (km)	20	25	30	20	25	30
	employed	employed	employed	inc/ adult	inc/ adult	inc/ adult
Big Storm	-0.010***	-0.004	-0.004	-0.070***	-0.052***	-0.034*
	(0.003)	(0.004)	(0.003)	(0.017)	(0.017)	(0.017)
Small Storm	0.002	0.001	0.003	-0.005	-0.012	-0.007
	(0.002)	(0.002)	(0.002)	(0.009)	(0.010)	(0.010)
Observations	21,064	21,064	21,064	20,808	20,808	20,808
R-squared	0.021	0.021	0.021	0.073	0.072	0.072
Panel B: Smoothing paramater b = 2.2						
Radius (km)	20	25	30	20	25	30
	employed	employed	employed	inc/ adult	inc/ adult	inc/ adult
Big Storm	-0.010***	-0.005	-0.002	-0.071***	-0.067***	-0.054***
	(0.003)	(0.004)	(0.004)	(0.017)	(0.018)	(0.017)
Small Storm	0.001	0.002	0.002	-0.009	-0.008	-0.004
	(0.002)	(0.002)	(0.002)	(0.009)	(0.010)	(0.010)
Observations	21,064	21,064	21,064	20,808	20,808	20,808
R-squared	0.021	0.021	0.021	0.073	0.073	0.072
Panel C: Smoothing paramater b = 2.0						
Radius (km)	20	25	30	20	25	30
	employed	employed	employed	inc/ adult	inc/ adult	inc/ adult
Big Storm	-0.006	-0.006	-0.003	-0.065***	-0.072***	-0.061***
	(0.004)	(0.004)	(0.004)	(0.019)	(0.020)	(0.018)
Small Storm	0.000	0.002	0.002	-0.011	-0.007	-0.006
	(0.002)	(0.002)	(0.002)	(0.009)	(0.010)	(0.010)
Observations	21,064	21,064	21,064	20,808	20,808	20,808
R-squared	0.021	0.021	0.021	0.072	0.073	0.072

This table replicates the main regressions using the chosen specification (Column 4 of Table 3), but for different storm model parameter choices. We do this for both total employment (Columns 1-3), and average income per adult (Columns 4-6). Panel A, B, C show results with storms parameters with a smoothing parameter 'b' set to 2.4, 2.2, 2.0 respectively. Moving across columns we interate the radius parameter 'r', looking at 20km, 25km, and 30km. For example Panel B, Column (5), shows the impact on wages of storms parameterized with b=2.2, r=25, which is our chosen specification in Table 3.

Table A.2: Replication of Main Individual Results (Income and Employment) with Alternative Storm Paramaterizations

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Smoothing paramater b = 2.4						
Radius (km)	20	25	30	20	25	30
	employed	employed	employed	wage/ week	wage/ week	wage/ week
Big Storm	-0.010***	-0.004	-0.005*	-0.032***	-0.015	-0.018**
	(0.003)	(0.003)	(0.002)	(0.009)	(0.009)	(0.008)
Small Storm	0.002	0.001	0.002	-0.008	-0.005	-0.002
	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Observations	2,464,172	2,464,172	2,464,172	660,650	660,650	660,650
R-squared	0.219	0.219	0.219	0.446	0.446	0.446
Panel B: Smoothing paramater b = 2.2						
Radius (km)	20	25	30	20	25	30
	employed	employed	employed	wage/ week	wage/ week	wage/ week
Big Storm	-0.009***	-0.005*	-0.002	-0.031***	-0.021**	-0.021**
	(0.003)	(0.003)	(0.003)	(0.010)	(0.009)	(0.009)
Small Storm	0.001	0.002	0.002	-0.008*	-0.004	-0.003
	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Observations	2,464,172	2,464,172	2,464,172	660,650	660,650	660,650
R-squared	0.219	0.219	0.219	0.446	0.446	0.446
Panel C: Smoothing paramater b = 2.0						
Radius (km)	20	25	30	20	25	30
	employed	employed	employed	wage/ week	wage/ week	wage/ week
Big Storm	-0.006*	-0.006*	-0.003	-0.024**	-0.019*	-0.021**
	(0.004)	(0.003)	(0.003)	(0.010)	(0.010)	(0.010)
Small Storm	0.000	0.002	0.002	-0.009*	-0.004	-0.003
	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Observations	2,464,172	2,464,172	2,464,172	660,650	660,650	660,650
R-squared	0.219	0.219	0.219	0.446	0.446	0.446

This table replicates the main regressions using the chosen specification (Column 4 of Table 5), but for different storm model parameter choices. We do this for both total employment (Columns 1-3), and average income per adult (Columns 4-6). Panel A, B, C show results with storms parameters with a smoothing parameter ‘b’ set to 2.4, 2.2, 2.0 respectively. Moving across columns we interate the radius parameter ‘r’, looking at 20km, 25km, and 30km. For example Panel B, Column (5), shows the impact on wages of storms parameterized with b=2.2, r=25, which is our chosen specification in Table 5.

Aggregate decomposition with multiple different parameter choices

Table A.3: Aggregrate Decomposition: Parameterization: b=2, r = 20km

	(1) inc/ adult	(2) wage/ week	(3) wage/ hour	(4) hours/ earner	(5) earners/ job	(6) job/ adult
Big Storm	-0.065***	-0.037***	-0.023**	-0.013	-0.018	-0.010
	(0.019)	(0.013)	(0.011)	(0.009)	(0.020)	(0.007)
Small Storm	-0.011	-0.012*	-0.011**	-0.001	0.002	-0.001
	(0.009)	(0.007)	(0.005)	(0.004)	(0.008)	(0.004)
Denominator	Adults	Earners	Earned Hours	Earners	Jobs	Adults
Observations	20,808	20,808	20,808	20,808	20,808	20,808
R-squared	0.072	0.131	0.146	0.068	0.024	0.016

This Table replicates the decomposition of wage impacts in the aggregate data (Table 4), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 4 in the main text.

Table A.4: Aggregrate Decomposition: Parameterization: b=2, r = 25km

	(1) inc/ adult	(2) wage/ week	(3) wage/ hour	(4) hours/ earner	(5) earners/ job	(6) job/ adult
Big Storm	-0.072***	-0.034**	-0.023**	-0.011	-0.028	-0.009
	(0.020)	(0.013)	(0.009)	(0.009)	(0.020)	(0.007)
Small Storm	-0.007	-0.014**	-0.010**	-0.003	0.003	0.003
	(0.010)	(0.006)	(0.005)	(0.004)	(0.007)	(0.003)
Denominator	Adults	Earners	Earned Hours	Earners	Jobs	Adults
Observations	20,808	20,808	20,808	20,808	20,808	20,808
R-squared	0.073	0.131	0.146	0.068	0.024	0.016

This Table replicates the decomposition of wage impacts in the aggregate data (Table 4), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 4 in the main text.

Table A.5: Aggregrate Decomposition: Parameterization: b=2, r = 30km

	(1) inc/ adult	(2) wage/ week	(3) wage/ hour	(4) hours/ earner	(5) earners/ job	(6) job/ adult
Big Storm	-0.061***	-0.032***	-0.024***	-0.008	-0.024	-0.005
	(0.018)	(0.012)	(0.008)	(0.008)	(0.016)	(0.006)
Small Storm	-0.006	-0.011*	-0.008	-0.004	0.003	0.003
	(0.010)	(0.006)	(0.005)	(0.004)	(0.008)	(0.003)
Denominator	Adults	Earners	Earned Hours	Earners	Jobs	Adults
Observations	20,808	20,808	20,808	20,808	20,808	20,808
R-squared	0.072	0.131	0.146	0.068	0.024	0.016

This Table replicates the decomposition of wage impacts in the aggregate data (Table 4), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 4 in the main text.

Table A.6: Aggregrate Decomposition: Parameterization: b=2.2, r = 20km

	(1) inc/ adult	(2) wage/ week	(3) wage/ hour	(4) hours/ earner	(5) earners/ job	(6) job/ adult
Big Storm	-0.071***	-0.037***	-0.024***	-0.014	-0.019	-0.015**
	(0.017)	(0.011)	(0.009)	(0.008)	(0.017)	(0.006)
Small Storm	-0.009	-0.013*	-0.012**	-0.001	0.003	0.001
	(0.009)	(0.007)	(0.005)	(0.004)	(0.007)	(0.004)
Denominator	Adults	Earners	Earned Hours	Earners	Jobs	Adults
Observations	20,808	20,808	20,808	20,808	20,808	20,808
R-squared	0.073	0.131	0.146	0.068	0.024	0.016

This Table replicates the decomposition of wage impacts in the aggregate data (Table 4), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 4 in the main text.

Table A.7: Aggregrate Decomposition: Parameterization: b=2.2, r = 25km

	(1) inc/ adult	(2) wage/ week	(3) wage/ hour	(4) hours/ earner	(5) earners/ job	(6) job/ adult
Big Storm	-0.067***	-0.036***	-0.025***	-0.011	-0.023	-0.008
	(0.018)	(0.011)	(0.009)	(0.009)	(0.017)	(0.006)
Small Storm	-0.008	-0.014**	-0.010*	-0.003	0.003	0.002
	(0.010)	(0.007)	(0.005)	(0.004)	(0.008)	(0.003)
Denominator	Adults	Earners	Earned Hours	Earners	Jobs	Adults
Observations	20,808	20,808	20,808	20,808	20,808	20,808
R-squared	0.073	0.131	0.146	0.068	0.024	0.016

This Table replicates the decomposition of wage impacts in the aggregate data (Table 4), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 4 in the main text.

Table A.8: Aggregrate Decomposition: Parameterization: b=2.2, r = 30km

	(1) inc/ adult	(2) wage/ week	(3) wage/ hour	(4) hours/ earner	(5) earners/ job	(6) job/ adult
Big Storm	-0.054***	-0.032**	-0.026***	-0.006	-0.019	-0.004
	(0.017)	(0.012)	(0.009)	(0.008)	(0.015)	(0.006)
Small Storm	-0.004	-0.010	-0.007	-0.003	0.003	0.003
	(0.010)	(0.006)	(0.005)	(0.004)	(0.008)	(0.003)
Denominator	Adults	Earners	Earned Hours	Earners	Jobs	Adults
Observations	20,808	20,808	20,808	20,808	20,808	20,808
R-squared	0.072	0.131	0.146	0.068	0.024	0.016

This Table replicates the decomposition of wage impacts in the aggregate data (Table 4), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 4 in the main text.

Table A.9: Aggregrate Decomposition: Parameterization: b=2.4, r = 20km

	(1) inc/ adult	(2) wage/ week	(3) wage/ hour	(4) hours/ earner	(5) earners/ job	(6) job/ adult
Big Storm	-0.070***	-0.036***	-0.022***	-0.013*	-0.019	-0.016***
	(0.017)	(0.011)	(0.008)	(0.008)	(0.016)	(0.006)
Small Storm	-0.005	-0.011*	-0.011**	-0.001	0.004	0.002
	(0.009)	(0.007)	(0.005)	(0.004)	(0.008)	(0.004)
Denominator	Adults	Earners	Earned Hours	Earners	Jobs	Adults
Observations	20,808	20,808	20,808	20,808	20,808	20,808
R-squared	0.073	0.131	0.146	0.068	0.024	0.017

This Table replicates the decomposition of wage impacts in the aggregate data (Table 4), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 4 in the main text.

Table A.10: Aggregrate Decomposition: Parameterization: b=2.4, r = 25km

	(1) inc/ adult	(2) wage/ week	(3) wage/ hour	(4) hours/ earner	(5) earners/ job	(6) job/ adult
Big Storm	-0.052***	-0.034***	-0.023***	-0.012	-0.012	-0.006
	(0.017)	(0.010)	(0.008)	(0.008)	(0.016)	(0.006)
Small Storm	-0.012	-0.014**	-0.010*	-0.004	0.000	0.002
	(0.010)	(0.007)	(0.005)	(0.003)	(0.008)	(0.003)
Denominator	Adults	Earners	Earned Hours	Earners	Jobs	Adults
Observations	20,808	20,808	20,808	20,808	20,808	20,808
R-squared	0.072	0.131	0.146	0.068	0.024	0.016

This Table replicates the decomposition of wage impacts in the aggregate data (Table 4), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 4 in the main text.

Table A.11: Aggregrate Decomposition: Parameterization: b=2.4, r = 30km

	(1) inc/ adult	(2) wage/ week	(3) wage/ hour	(4) hours/ earner	(5) earners/ job	(6) job/ adult
Big Storm	-0.034*	-0.020**	-0.016**	-0.004	-0.007	-0.007
	(0.017)	(0.010)	(0.007)	(0.006)	(0.014)	(0.004)
Small Storm	-0.007	-0.013**	-0.010*	-0.004	0.002	0.004
	(0.010)	(0.006)	(0.005)	(0.004)	(0.008)	(0.004)
Denominator	Adults	Earners	Earned Hours	Earners	Jobs	Adults
Observations	20,808	20,808	20,808	20,808	20,808	20,808
R-squared	0.072	0.131	0.146	0.067	0.024	0.016

This Table replicates the decomposition of wage impacts in the aggregate data (Table 4), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 4 in the main text.

Individual decomposition with multiple different parameter choices

Table A.12: Indivividual Decomposition: Parameterization: b=2.2, r = 20km

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact on Intensive Margins (Earnings and Hours)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.031***	-0.015*	-0.013*	-0.017**	-0.012*	-0.001
	(0.010)	(0.008)	(0.008)	(0.007)	(0.007)	(0.003)
Small Storm	-0.008*	-0.009**	-0.003	-0.006	-0.001	-0.002
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	660,650	1,430,357	660,650	660,650	660,650	660,650
R-squared	0.446	0.128	0.094	0.417	0.093	0.039
Panel B: Impact on Extensive Margins						
	employed	job	wage missing	wage observed	zero hours	lost job quarter
Big Storm	-0.009***	-0.008***	0.002	-0.005	0.001	0.000
	(0.003)	(0.003)	(0.005)	(0.003)	(0.001)	(0.002)
Small Storm	0.001	0.001	-0.001	0.001	0.000	-0.002***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)
Sample	All	All	Earners	All	All	All
Observations	2,464,172	2,464,172	1,430,353	2,464,172	2,464,172	2,464,172
R-squared	0.219	0.228	0.188	0.097	0.015	0.021
Mean Dep. Var	0.573	0.581	0.507	0.286	0.009	0.030

This Table replicates the decomposition of wage impacts in the aggregate data (Table 6), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 6 in the main text.

Table A.13: Indivividual Decomposition: Parameterization: b=2.2, r = 25km

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact on Intensive Margins (Earnings and Hours)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.021**	-0.010	-0.007	-0.014**	-0.006	-0.001
	(0.009)	(0.008)	(0.007)	(0.007)	(0.006)	(0.004)
Small Storm	-0.004	-0.006	-0.002	-0.002	0.001	-0.004*
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	660,650	1,430,357	660,650	660,650	660,650	660,650
R-squared	0.446	0.128	0.094	0.417	0.093	0.039
Panel B: Impact on Extensive Margins						
	employed	job	wage missing	wage observed	zero hours	lost job quarter
Big Storm	-0.005*	-0.004	0.005	-0.005	0.001	0.001
	(0.003)	(0.003)	(0.005)	(0.003)	(0.001)	(0.002)
Small Storm	0.002	0.002	-0.001	0.002	0.000	-0.003***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)
Sample	All	All	Earners	All	All	All
Observations	2,464,172	2,464,172	1,430,353	2,464,172	2,464,172	2,464,172
R-squared	0.219	0.228	0.188	0.097	0.015	0.021
Mean Dep. Var	0.573	0.581	0.507	0.286	0.009	0.030

This Table replicates the decomposition of wage impacts in the aggregate data (Table 6), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 6 in the main text.

Table A.14: Indivividual Decomposition: Parameterization: b=2.2, r = 30km

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact on Intensive Margins (Earnings and Hours)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.021**	-0.005	-0.004	-0.017**	-0.004	0.000
	(0.009)	(0.007)	(0.007)	(0.007)	(0.006)	(0.003)
Small Storm	-0.003	-0.005	-0.003	0.000	0.003	-0.006***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	660,650	1,430,357	660,650	660,650	660,650	660,650
R-squared	0.446	0.128	0.094	0.417	0.093	0.039
Panel B: Impact on Extensive Margins						
	employed	job	wage missing	wage observed	zero hours	lost job quarter
Big Storm	-0.002	-0.002	0.003	-0.002	0.000	0.001
	(0.003)	(0.003)	(0.004)	(0.003)	(0.001)	(0.002)
Small Storm	0.002	0.002	0.000	0.001	0.000	-0.003***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)
Sample	All	All	Earners	All	All	All
Observations	2,464,172	2,464,172	1,430,353	2,464,172	2,464,172	2,464,172
R-squared	0.219	0.228	0.188	0.097	0.015	0.021
Mean Dep. Var	0.573	0.581	0.507	0.286	0.009	0.030

This Table replicates the decomposition of wage impacts in the aggregate data (Table 6), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 6 in the main text.

Table A.15: Indivividual Decomposition: Parameterization: b=2.4, r = 20km

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact on Intensive Margins (Earnings and Hours)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.032***	-0.015**	-0.015**	-0.017**	-0.011*	-0.004
	(0.009)	(0.007)	(0.007)	(0.007)	(0.006)	(0.003)
Small Storm	-0.008	-0.010**	-0.002	-0.005	-0.001	-0.001
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	660,650	1,430,357	660,650	660,650	660,650	660,650
R-squared	0.446	0.128	0.094	0.417	0.093	0.039
Panel B: Impact on Extensive Margins						
	employed	job	wage missing	wage observed	zero hours	lost job quarter
Big Storm	-0.010***	-0.009***	0.002	-0.006*	0.001	0.000
	(0.003)	(0.003)	(0.005)	(0.003)	(0.001)	(0.002)
Small Storm	0.002	0.002	-0.001	0.001	0.000	-0.002**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)
Sample	All	All	Earners	All	All	All
Observations	2,464,172	2,464,172	1,430,353	2,464,172	2,464,172	2,464,172
R-squared	0.219	0.228	0.188	0.097	0.015	0.021
Mean Dep. Var	0.573	0.581	0.507	0.286	0.009	0.030

This Table replicates the decomposition of wage impacts in the aggregate data (Table 6), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 6 in the main text.

Table A.16: Indivividual Decomposition: Parameterization: b=2.4, r = 25km

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact on Intensive Margins (Earnings and Hours)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.015	-0.008	-0.008	-0.007	-0.006	-0.002
	(0.009)	(0.008)	(0.007)	(0.007)	(0.005)	(0.004)
Small Storm	-0.005	-0.008*	-0.003	-0.002	0.001	-0.005**
	(0.005)	(0.004)	(0.004)	(0.005)	(0.003)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	660,650	1,430,357	660,650	660,650	660,650	660,650
R-squared	0.446	0.128	0.094	0.417	0.093	0.039
Panel B: Impact on Extensive Margins						
	employed	job	wage missing	wage observed	zero hours	lost job quarter
Big Storm	-0.003	-0.003	0.003	-0.003	0.001	0.000
	(0.003)	(0.003)	(0.005)	(0.003)	(0.001)	(0.002)
Small Storm	0.001	0.001	0.000	0.001	0.000	-0.003***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)
Sample	All	All	Earners	All	All	All
Observations	2,464,172	2,464,172	1,430,353	2,464,172	2,464,172	2,464,172
R-squared	0.219	0.228	0.188	0.097	0.015	0.021
Mean Dep. Var	0.573	0.581	0.507	0.286	0.009	0.030

This Table replicates the decomposition of wage impacts in the aggregate data (Table 6), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 6 in the main text.

Table A.17: Indivividual Decomposition: Parameterization: b=2.4, r = 30km

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact on Intensive Margins (Earnings and Hours)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.017**	-0.007	-0.005	-0.011*	-0.004	-0.002
	(0.008)	(0.006)	(0.006)	(0.006)	(0.005)	(0.003)
Small Storm	-0.002	-0.004	-0.002	0.000	0.004	-0.006***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	660,650	1,430,357	660,650	660,650	660,650	660,650
R-squared	0.446	0.128	0.094	0.417	0.093	0.039
Panel B: Impact on Extensive Margins						
	employed	job	wage missing	wage observed	zero hours	lost job quarter
Big Storm	-0.005*	-0.004*	-0.001	-0.001	0.000	0.000
	(0.002)	(0.002)	(0.004)	(0.003)	(0.001)	(0.001)
Small Storm	0.002	0.003	0.000	0.001	0.000	-0.002***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)
Sample	All	All	Earners	All	All	All
Observations	2,464,172	2,464,172	1,430,353	2,464,172	2,464,172	2,464,172
R-squared	0.219	0.228	0.188	0.097	0.015	0.021
Mean Dep. Var	0.573	0.581	0.507	0.286	0.009	0.030

This Table replicates the decomposition of wage impacts in the aggregate data (Table 6), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 6 in the main text.

Table A.18: Indivividual Decomposition: Parameterization: b=2, r = 20km

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact on Intensive Margins (Earnings and Hours)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.024**	-0.012	-0.011	-0.013*	-0.012*	0.000
	(0.010)	(0.009)	(0.008)	(0.007)	(0.007)	(0.004)
Small Storm	-0.009*	-0.009**	-0.003	-0.006	-0.001	-0.002
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	660,650	1,430,357	660,650	660,650	660,650	660,650
R-squared	0.446	0.128	0.094	0.417	0.093	0.039
Panel B: Impact on Extensive Margins						
	employed	job	wage missing	wage observed	zero hours	lost job quarter
Big Storm	-0.006*	-0.005	0.003	-0.004	0.001	0.001
	(0.004)	(0.003)	(0.005)	(0.003)	(0.001)	(0.002)
Small Storm	0.000	0.000	0.000	0.000	0.000	-0.002***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)
Sample	All	All	Earners	All	All	All
Observations	2,464,172	2,464,172	1,430,353	2,464,172	2,464,172	2,464,172
R-squared	0.219	0.228	0.188	0.097	0.015	0.021
Mean Dep. Var	0.573	0.581	0.507	0.286	0.009	0.030

This Table replicates the decomposition of wage impacts in the aggregate data (Table 6), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 6 in the main text.

Table A.19: Indivividual Decomposition: Parameterization: b=2, r = 25km

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact on Intensive Margins (Earnings and Hours)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.019*	-0.009	-0.007	-0.012*	-0.007	0.000
	(0.010)	(0.008)	(0.008)	(0.007)	(0.006)	(0.004)
Small Storm	-0.004	-0.006	-0.002	-0.003	0.002	-0.004*
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	660,650	1,430,357	660,650	660,650	660,650	660,650
R-squared	0.446	0.128	0.094	0.417	0.093	0.039
Panel B: Impact on Extensive Margins						
	employed	job	wage missing	wage observed	zero hours	lost job quarter
Big Storm	-0.006*	-0.005	0.006	-0.006*	0.001	0.001
	(0.003)	(0.003)	(0.005)	(0.003)	(0.001)	(0.002)
Small Storm	0.002	0.002	-0.001	0.001	0.000	-0.003***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)
Sample	All	All	Earners	All	All	All
Observations	2,464,172	2,464,172	1,430,353	2,464,172	2,464,172	2,464,172
R-squared	0.219	0.228	0.188	0.097	0.015	0.021
Mean Dep. Var	0.573	0.581	0.507	0.286	0.009	0.030

This Table replicates the decomposition of wage impacts in the aggregate data (Table 6), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 6 in the main text.

Table A.20: Indivividual Decomposition: Parameterization: b=2, r = 30km

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact on Intensive Margins (Earnings and Hours)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.021**	-0.009	-0.007	-0.014**	-0.004	-0.003
	(0.010)	(0.008)	(0.007)	(0.007)	(0.006)	(0.003)
Small Storm	-0.003	-0.004	-0.002	0.000	0.004	-0.006***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	660,650	1,430,357	660,650	660,650	660,650	660,650
R-squared	0.446	0.128	0.094	0.417	0.093	0.039
Panel B: Impact on Extensive Margins						
	employed	job	wage missing	wage observed	zero hours	lost job quarter
Big Storm	-0.003	-0.002	0.004	-0.004	0.001	0.001
	(0.003)	(0.003)	(0.005)	(0.003)	(0.001)	(0.002)
Small Storm	0.002	0.002	-0.001	0.002	0.000	-0.002***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)
Sample	All	All	Earners	All	All	All
Observations	2,464,172	2,464,172	1,430,353	2,464,172	2,464,172	2,464,172
R-squared	0.219	0.228	0.188	0.097	0.015	0.021
Mean Dep. Var	0.573	0.581	0.507	0.286	0.009	0.030

This Table replicates the decomposition of wage impacts in the aggregate data (Table 6), using a different storm parameterization. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). For more details see Table 6 in the main text.

Table A.21: Storm robust aggregate (updated with new parameters)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dropped storm:	Chebi	Cimaron	Durian	Fengshen	Imbudo	Linfa	Nida	Utor	Nanmadol	Xangsane
Panel A: Impact on Employment (with month of named storm dropped)										
Big Storm	-0.008*	-0.005	-0.008*	-0.004	-0.005	-0.005	-0.006	-0.008*	-0.003	-0.005
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Small Storm	0.002	0.002	0.002	0.002	0.001	0.001	0.002	0.002	0.002	0.002
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Observations	20,253	20,254	20,253	20,254	20,253	20,253	20,254	20,253	20,254	20,254
R-squared	0.021	0.021	0.021	0.022	0.022	0.022	0.021	0.021	0.021	0.021
Panel B: Impact on Per Capita Earnings (with month of named storm dropped)										
Big Storm	-0.051*	-0.089***	-0.051*	-0.072***	-0.065***	-0.065***	-0.067***	-0.051*	-0.055***	-0.089***
	(0.027)	(0.021)	(0.027)	(0.019)	(0.017)	(0.017)	(0.018)	(0.027)	(0.016)	(0.021)
Small Storm	-0.003	-0.021*	-0.003	0.000	-0.007	-0.007	-0.007	-0.003	-0.004	-0.021*
	(0.011)	(0.011)	(0.011)	(0.009)	(0.010)	(0.010)	(0.009)	(0.011)	(0.010)	(0.011)
Observations	20,009	20,008	20,009	20,005	20,000	20,000	20,005	20,009	20,008	20,008
R-squared	0.074	0.076	0.074	0.071	0.074	0.074	0.075	0.074	0.074	0.076

This Table replicates the main results in Table 3 (Column 4), for both employment (Panel A) and wages (Panel B). In each column, we drop the time periods during which the country was hit by each of the largest ten storms to have hit during the time period of the study. The Column headers give the name of the large dropped storm. For more details of the estimation, see Table 3 (Column 4). For details of when the named storms hit, and the damage it was reported to have rendered, see Table A.54.

Table A.22: Storm robust individual (updated with new parameters)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dropped storm:	Chebi	Cimaron	Durian	Fengshen	Imbudo	Linfa	Nida	Utor	Nanmadol	Xangsane
Panel A: Impact on Employment (with month of named storm dropped)										
Big Storm	-0.008**	-0.005	-0.008**	-0.004	-0.005	-0.005	-0.006*	-0.008**	-0.004	-0.005
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
Small Storm	0.002	0.002	0.002	0.002	0.001	0.001	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	2,372,710	2,370,435	2,372,710	2,372,809	2,365,039	2,365,039	2,369,784	2,372,710	2,367,676	2,370,435
R-squared	0.220	0.219	0.220	0.219	0.220	0.220	0.219	0.220	0.219	0.219
Panel B: Impact on Per Capita Earnings (with month of named storm dropped)										
Big Storm	-0.023**	-0.022*	-0.023**	-0.018*	-0.025**	-0.025**	-0.020**	-0.023**	-0.017*	-0.022*
	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)	(0.010)	(0.009)	(0.012)	(0.009)	(0.012)
Small Storm	-0.002	-0.005	-0.002	-0.004	-0.005	-0.005	-0.004	-0.002	-0.003	-0.005
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
Observations	635,125	636,483	635,125	635,661	631,921	631,921	633,558	635,125	634,966	636,483
R-squared	0.445	0.445	0.445	0.445	0.446	0.446	0.446	0.445	0.446	0.445

This Table replicates the main results in Table 5 (Column 4), for both employment (Panel A) and wages (Panel B). In each column, we drop the time periods during which the country was hit by each of the largest ten storms to have hit during the time period of the study. The Column headers give the name of the large dropped storm. For more details of the estimation, see Table 5 (Column 4). For details of when the named storms hit, and the damage it was reported to have rendered, see Table A.54.

Table A.23: Aggregate-level results (income per capita): Alternative storm measures

	(1) inc/ adult	(2) inc/ adult	(3) inc/ adult	(4) inc/ adult
Wind-speed (knots)	-0.00025*			
	(0.000)			
Normalized Wind-speed (0-1)		-0.078***		
		(0.028)		
ss scale 1			-0.003	
			(0.013)	
ss scale 2			-0.019	
			(0.014)	
ss scale 3			-0.003	
			(0.013)	
ss scale 4			-0.071***	
			(0.018)	
ss scale 5			-0.042	
			(0.050)	
Big Storm				-0.067***
				(0.018)
Small Storm				-0.007
				(0.009)
Observations	20,808	20,808	20,808	20,808
R-squared	0.072	0.072	0.073	0.073
Mean Dep. Var	5.400	5.400	5.400	5.400

Notes: Results from weighted municipal*quarter regressions. The dependent variable is the log of total income per capita for the municipality. Regressions control for municipal fixed effects, region-specified time fixed effects) as well as the share of the working age population in each education category, the share of women in the working age population, the number of men, the number of women, the number men age 15-30 and the number of women age 15-30. The standard errors (in parentheses) account for potential correlation within province. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.24: Aggregate-level results (employment): Alternative storm measures

	(1) employed	(2) employed	(3) employed	(4) employed
Wind-speed (knots)	0.000			
	(0.000)			
Normalized Wind-speed (0-1)		-0.006		
		(0.006)		
ss scale 1			0.003	
			(0.003)	
ss scale 2			0.002	
			(0.004)	
ss scale 3			0.000	
			(0.003)	
ss scale 4			-0.006	
			(0.004)	
ss scale 5			-0.004	
			(0.005)	
Big Storm				-0.005
				(0.004)
Small Storm				0.002
				(0.002)
Observations	21,064	21,064	21,064	21,064
R-squared	0.021	0.021	0.021	0.021
Mean Dep. Var	0.600	0.600	0.600	0.600

Notes: Results from weighted municipal*quarter regressions. The dependent variable is the employment rate in the municipality. Regressions control for municipal fixed effects, region-specified time fixed effects) as well as the share of the working age population in each education category, the share of women in the working age population, the number of men, the number of women, the number men age 15-30 and the number of women age 15-30. The standard errors (in parentheses) account for potential correlation within province. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.25: Impact of storm dispersion

	(1)	(2)	(3)	(4)	(5)
Panel A: Impact on Average Wages					
Big Storm	-0.067***			-0.076***	-0.061***
	(0.018)			(0.018)	(0.021)
Small Storm	-0.008			-0.019*	-0.004
	(0.010)			(0.010)	(0.013)
Num. Municapilities Effected		0.000		0.000**	
		(0.000)		(0.000)	
Wide storm			-0.024**		-0.008
			(0.010)		(0.013)
Narrow storm			0.019		0.044
			(0.065)		(0.071)
Observations	20,808	20,808	20,808	20,808	20,808
R-squared	0.073	0.072	0.072	0.073	0.073
Mean Dep. Var	5.300	5.300	5.300	5.300	5.300
Storm survey	Yes	Yes	Yes	Yes	Yes
Panel B: Impact on Employment					
Big Storm	-0.005			-0.005	-0.002
	(0.004)			(0.004)	(0.005)
Small Storm	0.002			0.002	0.003
	(0.002)			(0.003)	(0.003)
Num. Municapilities Effected		0.000		0.000	
		(0.000)		(0.000)	
Wide storm			-0.001		-0.003
			(0.002)		(0.003)
Narrow storm			-0.013		-0.015
			(0.013)		(0.014)
Observations	21,064	21,064	21,064	21,064	21,064
R-squared	0.021	0.021	0.021	0.021	0.021
Mean Dep. Var	0.600	0.600	0.600	0.600	0.600
Storm survey	Yes	Yes	Yes	Yes	Yes

Notes: Table shows the impact of storms on Wages (Panel A) and Employment (Panel B). In Column (1) we replicate the main findings in Table 3 (Column 4). In Column 2 we estimate the pure effect of the number of municipalities that registered any windspeed attritbutable to a given storm. In Column 3 we estimate the impact of Wide storms and Narrow storms, where wide storms are defined as those that hit more than median number of municipalities, among the number of municipalities hit by super typhoons that hit the country during the time period of the study. In Columns 4 and 5 we reestimate the effect of Big and Small storms (categorized in terms of windspeed), controlling for the storm outcomes used in Columns 2 and 3 respectively.

Table A.26: Decomposition: heterogeneity by storm speed

	(1) inc/ adult	(2) wage/ week	(3) wage/ hour	(4) hours/ earner	(5) earners/ job	(6) job/ adult
Big Storm * slow	-0.027	-0.005	-0.008	0.003	-0.007	-0.015
	(0.031)	(0.029)	(0.025)	(0.016)	(0.026)	(0.009)
Big Storm	-0.054**	-0.033**	-0.021	-0.012	-0.020	-0.001
	(0.022)	(0.016)	(0.014)	(0.012)	(0.021)	(0.006)
Small Storm * slow	-0.001	0.003	0.001	0.002	-0.001	-0.004
	(0.014)	(0.010)	(0.009)	(0.004)	(0.013)	(0.006)
Small Storm	-0.006	-0.015*	-0.010	-0.004	0.004	0.004
	(0.013)	(0.008)	(0.007)	(0.004)	(0.010)	(0.005)
Denominator	Adults	Earners	Earned Hours	Earners	Jobs	Adults
Observations	20,808	20,808	20,808	20,808	20,808	20,808
R-squared	0.073	0.131	0.146	0.068	0.024	0.016

Notes: We replicate Table 4, decomposing the main wage effects. Here we estimate the heterogeneous effects of storms that move slowly (regardless of winspeed). We define a storm as slow if the eye of that storm moved at a speed slower than the median speed among storms of similar strength (Big or Small storms, respectively). We then interact that measure with the storm size classifications. For more detail of the specifications, see Table 4 in the main text.

Table A.27: Impact of storm regularity

	(1)	(2)	(3)
Panel A: Impact on Average Wages			
Big Storm	-0.067***	-0.068**	-0.079***
	(0.018)	(0.027)	(0.024)
Small Storm	-0.008	-0.008	-0.008
	(0.010)	(0.010)	(0.010)
Big Storm * One Storm		0.003	
		(0.033)	
Small Storm * Few storms		-0.003	-0.002
		(0.026)	(0.026)
Big Storm * Few storms			0.029
			(0.040)
Observations	20,808	20,808	20,808
R-squared	0.073	0.073	0.073
Mean Dep. Var	5.300	5.300	5.300
Storm survey	Yes	Yes	Yes
Panel B: Impact on Employment			
Big Storm	-0.005	-0.009**	-0.007
	(0.004)	(0.004)	(0.005)
Small Storm	0.002	0.000	0.000
	(0.002)	(0.002)	(0.002)
Big Storm * One Storm		0.008	
		(0.007)	
Small Storm * Few storms		0.010	0.010
		(0.006)	(0.006)
Big Storm * Few storms			0.003
			(0.006)
Observations	21,064	21,064	21,064
R-squared	0.021	0.021	0.021
Mean Dep. Var	0.600	0.600	0.600
Storm survey	Yes	Yes	Yes

Notes: We replicate Table 3, estimating the impact of storms on wages and employment. Here we estimate the heterogeneous effects on municipalities that are hit regularly by typhoons. We define municipalities that been hit by only one Super Typhoon during the period, to test whether impacts are larger for those storms. Then we define a municipality as having experienced "few storms" if three or fewer storms (of any size) hit during the period of the study. We interact that with our storm strength measures to look for heterogeneous effects of different storm regularity.

Table A.28: Replication of Main Individual Results with only Household Heads

	(1)	(2)	(3)	(4)	(5)
Panel A: Impact on Employment Rate per Adult					
Big Storm	-0.007	-0.010*	-0.009**	-0.009**	-0.010*
	(0.008)	(0.005)	(0.005)	(0.005)	(0.006)
Small Storm	-0.031***	-0.005**	-0.002	-0.001	-0.003
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	1,085,879	1,085,879	1,085,879	782,057	719,963
R-squared	0.001	0.038	0.244	0.246	0.246
Mean Dep. Var	0.800	0.800	0.800	0.800	0.800
Panel B: Impact on Log Income per Adult					
Big Storm	-0.237***	-0.034**	-0.035**	-0.040***	-0.037*
	(0.040)	(0.015)	(0.014)	(0.014)	(0.020)
Small Storm	0.094***	-0.008	-0.005	-0.009	-0.008
	(0.019)	(0.006)	(0.006)	(0.006)	(0.007)
Observations	333,488	333,488	333,488	249,408	228,340
R-squared	0.013	0.248	0.405	0.406	0.407
Mean Dep. Var	7.100	7.100	7.100	7.100	7.100
Mun FE	No	Yes	Yes	Yes	Yes
Agg Contr	No	No	Yes	Yes	Yes
Mindanao Incl.	Yes	Yes	Yes	No	No
Storm survey	Yes	Yes	Yes	Yes	No

Notes: This table replicates our main results from Table 5, but with only household heads included in the analysis. See Table 5 for more details on the main specifications.

Table A.29: Replication of Main Individual Results with only Household Heads and their Spouses

	(1)	(2)	(3)	(4)	(5)
Panel A: Impact on Employment Rate per Adult					
	0.015*	-0.004	-0.004	-0.004	0.000
	(0.008)	(0.005)	(0.005)	(0.005)	(0.006)
Small Storm	-0.016***	-0.003	-0.001	0.000	-0.001
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	1,916,879	1,916,879	1,916,879	1,367,950	1,258,905
R-squared	0.001	0.026	0.225	0.216	0.216
Mean Dep. Var	0.700	0.700	0.700	0.700	0.700
Panel B: Impact on Log Income per Adult					
Big Storm	-0.281***	-0.051***	-0.039***	-0.045***	-0.047**
	(0.046)	(0.015)	(0.013)	(0.013)	(0.020)
Small Storm	0.063***	-0.013*	-0.008	-0.011*	-0.011
	(0.021)	(0.007)	(0.006)	(0.006)	(0.007)
Observations	469,903	469,903	469,903	354,043	324,675
R-squared	0.010	0.226	0.437	0.442	0.442
Mean Dep. Var	7.000	7.000	7.000	7.000	7.000
Mun FE	No	Yes	Yes	Yes	Yes
Agg Contr	No	No	Yes	Yes	Yes
Mindanao Incl.	Yes	Yes	Yes	No	No
Storm survey	Yes	Yes	Yes	Yes	No

Notes: This table replicates our main results from Table 5, but with only household heads and their spouses included in the analysis. See Table 5 for more details on the main specifications.

Table A.30: Impacts of storms on municipal level sample sizes (in logs)

	(1) Adults	(2) Households	(3) Total	(4) In Labour Force
Big Storm	0.001	0.006	0.008	-0.003
	(0.007)	(0.007)	(0.009)	(0.009)
Small Storm	-0.001	-0.002	-0.000	0.004
	(0.005)	(0.004)	(0.004)	(0.006)
Observations	21,064	21,064	21,064	21,064
R-squared	0.030	0.102	0.069	0.043
Controls	No	No	No	No

Notes: This table uses our main specification from Table 3 (Column 4), but here we study the impact on the sample sizes used in the analysis, at the municipality. We express these counts in logs, of Adults, Households, Total Population including children, and individuals who report being in the labour force. For more details of the specifications, see Table 3.

Table A.31: Individual-level results: persistence

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact of Lagged Storms on Earnings and Hours						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm						
current	-0.016*	-0.002	-0.005	-0.011*	-0.005	0.000
	(0.009)	(0.008)	(0.007)	(0.007)	(0.006)	(0.004)
lag 1	-0.011	0.003	-0.009	-0.002	-0.005	-0.004
	(0.011)	(0.008)	(0.009)	(0.008)	(0.007)	(0.004)
lag 2	0.009	0.020**	0.018**	-0.009	0.011	0.007*
	(0.010)	(0.008)	(0.008)	(0.008)	(0.007)	(0.004)
lag 3	-0.012	-0.005	-0.007	-0.005	-0.005	-0.003
	(0.010)	(0.009)	(0.009)	(0.008)	(0.007)	(0.004)
Small Storm (lags estimated but not displayed)						
current	0.000	-0.001	-0.001	0.002	0.002	-0.004*
	(0.005)	(0.004)	(0.004)	(0.005)	(0.003)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	860,809	2,006,022	860,809	860,809	860,809	860,809
R-squared	0.444	0.130	0.092	0.419	0.090	0.040
Panel B: Impact on Lagged Storms on Employment (Extensive Margins)						
	employed	job	wage missing	wage observed	zero hours	lost job quarter
Big Storm						
current	-0.005	-0.004	0.006	-0.005	0.001	0.002
	(0.003)	(0.003)	(0.005)	(0.003)	(0.001)	(0.002)
lag 1	0.001	-0.003	0.004	-0.002	-0.004***	-0.003
	(0.003)	(0.003)	(0.005)	(0.003)	(0.001)	(0.002)
lag 2	-0.002	-0.004	-0.007	0.002	-0.002**	0.000
	(0.003)	(0.003)	(0.005)	(0.003)	(0.001)	(0.002)
lag 3	-0.002	-0.003	0.006	-0.005	-0.001	0.001
	(0.003)	(0.003)	(0.005)	(0.003)	(0.001)	(0.002)
Small Storm (lags estimated but not displayed)						
current	0.000	0.001	0.001	0.000	0.000	-0.002***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)
Sample	All	All	Earners	All	All	All
Observations	3,402,456	3,402,456	2,006,018	3,402,456	3,402,456	3,402,456
R-squared	0.228	0.238	0.197	0.105	0.015	0.021
Mean Dep. Var	0.600	0.600	0.500	0.300	0.000	0.000

Notes: Results from weighted individual regressions. In Panel A, the dependent variable is the log weekly wage for employed individuals (Column 1), number of hours worked for employed individuals (Column 2), number of hours worked for employed individuals earning a wage (Column 3), hourly wage for employed individuals (Column 4), number of days worked for employed individuals earning a wage (Column 5), number of hours worked per day for employed individuals earning a wage (Column 6). In Panel B, the dependent variables are a series of dummies equal to one if: the individual is employed (Column 1), the individual has a job (Column 2), the individual is employed but their wage is not observed (Column 3), the individual reports a wage regardless of employment status (Column 4), the individual reports having a job but working zero hours in the last 7 days (Column 5), the individual reports not having a job now, but having worked in the last 3 months (Column 6). Regressions control for municipal fixed effects, time fixed effects as well as respondent's age, age square, education levels and gender. The standard errors (in parentheses) account for potential correlation within municipality. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.32: Panel-level results: Employment

	(1) employed	(2) job	(3) wage missing	(4) wage observed	(5) zero hours	(6) lost job quarter
Big Storm	-0.005	-0.004	0.009*	-0.007**	0.003	0.005
	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)	(0.005)
Small Storm	0.001	0.001	0.003	0.000	0.001	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Observations	1,294,842	1,294,842	792,550	1,294,842	805,430	489,412
R-squared	0.002	0.002	0.002	0.001	0.001	0.013
Mean Dep. Var	0.603	0.612	0.536	0.283	0.015	0.058

Notes: Results from weighted individual regressions. The dependent variables are a series of dummies equal to one if: the individual is employed (Column 1), the individual has a job (Column 2), the individual is employed but their wage is not observed (Column 3), the individual reports a wage regardless of employment status (Column 4), the individual reports having a job but working zero hours in the last 7 days (Column 5), the individual reports not having a job now, but having worked in the last 3 months (Column 6). Regressions control for time fixed effects as well as municipal fixed effects (Panel A) and individual fixed effects (Panel B). In Panel A, regression control for the respondent's age, age square, education levels and gender. The standard errors (in parentheses) account for potential correlation within municipality. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.33: Panel results: Comparison of municipal and individual fixed effects

	(1)	(2)	(3)	(4)
Panel B: All Employees				
	wage/ week	wage/ week	wage/ week	wage/ week
Big Storm	-0.017**	-0.020**	-0.021**	-0.024**
	(0.008)	(0.008)	(0.010)	(0.010)
Small Storm	-0.007	-0.009*	-0.003	-0.007
	(0.005)	(0.005)	(0.006)	(0.006)
Observations	349,605	267,038	349,605	267,038
R-squared	0.021	0.022	0.460	0.465
FE	Ind	Ind	Muni	Muni
Mindanao	Yes	No	Yes	No
Panel B: All Employees with similar jobs				
	wage/ week	wage/ week	wage/ week	wage/ week
Big Storm	-0.021**	-0.025**	-0.010	-0.014
	(0.009)	(0.010)	(0.013)	(0.014)
Small Storm	-0.005	-0.008	0.002	-0.001
	(0.005)	(0.006)	(0.008)	(0.008)
Observations	163,043	125,078	163,043	125,078
R-squared	0.020	0.021	0.519	0.523
FE	Ind	Ind	Muni	Muni
Mindanao	Yes	No	Yes	No

Notes: Results from weighted panel regressions. The dependent variable is the average weekly wage. Regressions control for individual fixed effects, region-specified time fixed effects as well as respondent's age, age square, education levels and gender. The standard errors (in parentheses) account for potential correlation within province. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.34: Panel-level results: Employment in different types of jobs

	(1)	(2)	(3)	(4)	(5)	(6)
	Self-	Private Sector		Farming		
	Employed	Permanent	Temporay	Own	Wage	Government
Panel A: Total Effect (Unconditional on having a job)						
Big Storm	0.000	0.007	0.003	0.000	-0.002	-0.007
	(0.001)	(0.008)	(0.006)	(0.001)	(0.007)	(0.005)
Small Storm	-0.001	-0.007	0.008**	0.000	0.000	0.000
	(0.001)	(0.004)	(0.004)	(0.000)	(0.003)	(0.003)
Observations	396,552	396,552	396,552	396,552	396,552	396,552
R-squared	0.005	0.148	0.039	0.044	0.293	0.066
Mean Dep. Var	0.004	0.502	0.170	0.002	0.160	0.149
Panel A: Composition Effect (Conditional on having a job)						
Big Storm	0.000	-0.001	-0.001	0.006	-0.002	-0.004
	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.002)
Small Storm	-0.001	-0.004	0.002	0.004	-0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Observations	805,430	805,430	805,430	805,430	805,430	805,430
R-squared	0.040	0.144	0.036	0.263	0.118	0.026
Mean Dep. Var	0.230	0.263	0.089	0.241	0.084	0.078
Panel C: Composition Effect (Conditional on earning a wage)						
Big Storm	-0.003	0.000	0.000	0.007	-0.002	-0.004
	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.002)
Small Storm	-0.002	-0.001	0.001	0.005*	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)
Observations	717,992	717,992	717,992	717,992	717,992	717,992
R-squared	0.040	0.156	0.032	0.267	0.119	0.029
Mean Dep. Var	0.141	0.161	0.054	0.148	0.051	0.048

Notes: Results from weighted individual regressions. The dependent variable is a dummy equal to one if the individual is: self-employed (Column 1), has a permanent job in the private sector (Column 2), has a temporary job in the private sector (Column 3), works on the family farm (Column 4), works for a wage on someone's else farm (Column 5), is employed in the public sector (Column 6). Regressions control for municipal fixed effects, time fixed effects as well as respondent's age, age square, education levels and gender. The standard errors (in parentheses) account for potential correlation within municipality. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.35: Panel-level results: Decomposition for workers who stay at similar jobs

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact on Earnings and Hours (Same Job Characteristics)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.021**	-0.015**	-0.012	-0.010	-0.007	-0.006
	(0.010)	(0.008)	(0.008)	(0.007)	(0.007)	(0.004)
Small Storm	-0.004	-0.006	-0.005	0.000	-0.002	-0.004
	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	157,273	410,445	157,963	157,273	157,962	157,962
R-squared	0.020	0.005	0.011	0.018	0.014	0.001
Panel B: Impact on Earnings and Hours (Same Job Characteristics, Payment Type)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.025**	-0.012	-0.012	-0.013*	-0.010	-0.002
	(0.010)	(0.008)	(0.008)	(0.007)	(0.007)	(0.004)
Small Storm	-0.008	-0.002	-0.002	-0.006	-0.002	-0.001
	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	125,078	125,098	125,087	125,078	125,087	125,087
R-squared	0.021	0.013	0.013	0.020	0.016	0.001

Notes: Results from weighted individual fixed-effects regressions. Panel A shows results for individuals who are working in at least two periods of the data, for who remain working at jobs of the same job type. Panel B shows results for workers whose stay at jobs that look identical in terms of job type, occupation, type of employer and method of payment. The dependent variable is the log weekly wage for employed individuals (Column 1), number of hours worked for employed individuals (Column 2), number of hours worked for employed individuals earning a wage (Column 3), hourly wage for employed individuals (Column 4), number of days worked for employed individuals earning a wage (Column 5), number of hours worked per day for employed individuals earning a wage (Column 6). Regressions control for time fixed effects and individual fixed effects. The standard errors (in parentheses) account for potential correlation within municipality. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.36: Aggregate-level decomposition: Heterogeneity for rural-urban areas

	(1) inc/ adult	(2) wage/ week	(3) wage/ hour	(4) hours/ earner	(5) earners/ job	(6) job/ adult
Big Storm	-0.068***	-0.039***	-0.026**	-0.013	-0.022	-0.006
	(0.019)	(0.013)	(0.010)	(0.009)	(0.016)	(0.007)
Big Storm * city	0.007	0.019	0.007	0.013	-0.005	-0.009
	(0.044)	(0.025)	(0.015)	(0.014)	(0.029)	(0.011)
Small Storm	-0.012	-0.011	-0.008	-0.003	0.000	0.000
	(0.011)	(0.007)	(0.006)	(0.004)	(0.009)	(0.004)
Small Storm * city	0.014	-0.004	-0.006	0.002	0.011	0.005
	(0.012)	(0.007)	(0.007)	(0.005)	(0.010)	(0.007)
Denominator	Adults	Earners	Earned Hours	Earners	Jobs	Adults
Observations	20,808	20,808	20,808	20,808	20,831	21,064
R-squared	0.073	0.131	0.146	0.068	0.024	0.016

Note: esults from weighted municipal*quarter regressions. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). Regressions control for municipal fixed effects, time fixed effects as well as the share of the working age population in each education category, the share of women in the working age population, the number of men, the number of women, the number men age 15-30 and the number of women age 15-30. The sample is restricted to municipalities outside of Mindanao. The standard errors (in parentheses) account for potential correlation within province. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.37: Individuals-level results: Heterogenous treatment effects by managerial and non-managerial private sector jobs) UPDATED

	(1) wage/ week	(2) hours/ worker	(3) hours/ earner	(4) wage/ hour	(5) days/ earner	(6) hours/ day
Big Storm * non manag	-0.025**	-0.026***	-0.011	-0.017**	-0.009	-0.002
	(0.010)	(0.009)	(0.009)	(0.008)	(0.007)	(0.004)
Small Storm * non manag	-0.004	-0.007	-0.003	-0.001	0.001	-0.005**
	(0.006)	(0.004)	(0.004)	(0.005)	(0.004)	(0.002)
Big Storm * manag	0.236***	0.138***	0.108***	0.114	0.059**	0.047**
	(0.069)	(0.020)	(0.036)	(0.072)	(0.023)	(0.019)
Small Storm * manag	-0.058*	0.001	-0.005	-0.041	-0.014	0.011
	(0.032)	(0.012)	(0.018)	(0.033)	(0.013)	(0.011)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	566,279	1,317,287	566,279	575,322	566,279	566,279
R-squared	0.464	0.157	0.101	0.414	0.101	0.045
Equality F-stat	14.011	56.066	9.582	3.267	7.352	6.185
Equality p-val	0.000	0.000	0.002	0.071	0.007	0.013

Notes: Results from weighted individual regressions. Sample is restricted to individuals working in the private sector. In Panel A, the dependent variable is the log weekly wage for employed individuals (Column 1), number of hours worked for employed individuals (Column 2), number of hours worked for employed individuals earning a wage (Column 3), hourly wage for employed individuals (Column 4), number of days worked for employed individuals earning a wage (Column 5), number of hours worked per day for employed individuals earning a wage (Column 6). Regressions control for municipal fixed effects, region-specified time fixed effects as well as respondent's age, age square, education levels and gender. Regression also include a full set of job type dummies. The standard errors (in parentheses) account for potential correlation within province. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.38: Impacts in levels: Comparison between individual and aggregated results

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Main Impacts in Levels for Aggregated Data						
	inc/ adult	wage/ worker	wage/ earner	hours/ adult	hours/ worker	hours/ earner
Big Storm	-15.098***	-19.717**	-28.558***	-0.453**	-0.316	-0.479
	(4.251)	(7.492)	(10.582)	(0.217)	(0.297)	(0.349)
Small Storm	5.675*	12.458**	4.096	-0.056	-0.131	-0.135
	(2.883)	(5.153)	(6.562)	(0.112)	(0.103)	(0.143)
Observations	21,064	21,064	20,831	21,064	21,064	20,831
R-squared	0.181	0.192	0.198	0.053	0.057	0.077
Mean Dep. Var	383.225	700.562	1,280.171	24.139	42.622	43.190
BStorm as % of Mean	-0.028	-0.026	-0.021	-0.014	-0.008	-0.008
Panel B: Main Impacts in Levels for Individual Data						
	inc/ adult	wage/ worker	wage/ earner	hours/ adult	hours/ worker	hours/ earner
Big Storm	-8.891**	-9.555	-11.348	-0.393**	-0.393*	-0.291
	(4.146)	(6.705)	(11.221)	(0.174)	(0.234)	(0.251)
Small Storm	12.301***	23.160***	26.624***	-0.006	-0.101	-0.081
	(3.321)	(5.465)	(7.115)	(0.095)	(0.119)	(0.128)
Observations	2,464,172	1,439,415	669,711	2,464,172	1,453,620	669,711
R-squared	0.061	0.167	0.174	0.013	0.110	0.072
Mean Dep. Var	391.800	680.000	1,370.700	24.100	41.500	44.700
BStorm as % of Mean	-0.023	-0.014	-0.008	-0.016	-0.009	-0.007

Notes: Results from weighted individual regressions. The dependent variables are: the income per adult in the sample. This is the total income divided by the total number of adults (Column 1), the wage per worker- the total wages divided by the total number of workers (Column 2), the wage per worker for whom a wage is observed (Column 3), hours per adult- the total hours worked divided by the number of adults (Column 4), total hours over the number of workers (Column 5) and the hours per worker for whom a wage is observed (Column 6). Regressions control for municipal fixed effects, region-specified time fixed effects as well as respondent's age, age square, education levels and gender. The standard errors (in parentheses) account for potential correlation within province. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.39: Panel-level results: decomposition (Table 9) with individual Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact on Earnings and Hours (All Employees)						
Big Storm	-0.020**	-0.021***	-0.015*	-0.007	-0.007	-0.009**
	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.004)
Small Storm	-0.009*	-0.007	-0.004	-0.004	-0.002	-0.002
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	267,038	699,704	277,932	267,038	277,928	277,928
R-squared	0.022	0.004	0.007	0.022	0.010	0.001
Panel B: Impact on Earnings and Hours (Same Job Type)						
Big Storm	-0.025**	-0.012	-0.012	-0.013*	-0.010	-0.002
	(0.010)	(0.008)	(0.008)	(0.007)	(0.007)	(0.004)
Small Storm	-0.008	-0.002	-0.002	-0.006	-0.002	-0.001
	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	125,078	125,098	125,087	125,078	125,087	125,087
R-squared	0.021	0.013	0.013	0.020	0.016	0.001

Notes: Results from weighted individual fixed-effects regressions. In Panel A, the dependent variable is the log weekly wage for employed individuals (Column 1), number of hours worked for employed individuals (Column 2), number of hours worked for employed individuals earning a wage (Column 3), hourly wage for employed individuals (Column 4), number of days worked for employed individuals earning a wage (Column 5), number of hours worked per day for employed individuals earning a wage (Column 6). In Panel B, the dependent variables are a series of dummies equal to one if: the individual is employed (Column 1), the individual has a job (Column 2), the individual is employed but their wage is not observed (Column 3), the individual reports a wage regardless of employment status (Column 4), the individual reports having a job but working zero hours in the last 7 days (Column 5), the individual reports not having a job now, but having worked in the last 3 months (Column 6). Regressions control for time fixed effects as well as municipal fixed effects (Panel A) and individual fixed effects (Panel B). In Panel A, regression control for the respondent's age, age square, education levels and gender. The standard errors (in parentheses) account for potential correlation within municipality. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Main results table from a previous draft, with parameters b = 1.8, r = 20km. Main Table counterpart number in paranthesis.

Table A.40: Aggregate-level results [Table 3] – Alternative Paramaterization

	(1)	(2)	(3)	(4)
Panel A: Impact on Employment Rate per Adult				
Big Storm	0.014	-0.005	-0.005	-0.007*
	(0.015)	(0.004)	(0.004)	(0.004)
Small Storm	-0.011	-0.001	-0.001	0.000
	(0.007)	(0.002)	(0.002)	(0.002)
Observations	29,560	29,560	29,560	21,064
R-squared	0.005	0.011	0.017	0.021
Mean Dep. Var	0.600	0.600	0.600	0.600
Panel B: Impact on Log Income per Adult				
Big Storm	-0.332***	-0.065***	-0.072***	-0.078***
	(0.091)	(0.022)	(0.023)	(0.024)
Small Storm	0.175***	-0.004	-0.004	-0.012
	(0.065)	(0.009)	(0.009)	(0.009)
Observations	28,608	28,608	28,608	20,808
R-squared	0.015	0.051	0.061	0.073
Mean Dep. Var	5.300	5.300	5.300	5.400
Mun FE	No	Yes	Yes	Yes
Agg Contr	No	No	Yes	Yes
Mindanao Incl.	Yes	Yes	Yes	No

Notes: Results from weighted municipal*quarter regressions. The dependent variable is the employment rate in the municipality (Panel A) and the average wage in the municipality (Panel B). Regressions control for time fixed effects (Column 1-4), municipal fixed effects (Column 2-4), as well as the share of the working age population in each education category, the share of women in the working age population, the number of men, the number of women, the number men age 15-30 and the number of women age 15-30 (Column 3-4). In Column 4, the sample is restricted to municipalities outside of Mindanao. The standard errors (in parentheses) account for potential correlation within province. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.41: Decomposing the aggregate-level effects [Table 4] – Alternative Paramaterization

	(1) inc/ adult	(2) wage/ week	(3) wage/ hour	(4) hours/ earner	(5) earners/ job	(6) job/ adult
Big Storm	-0.078***	-0.035**	-0.020*	-0.015*	-0.032	-0.011
	(0.024)	(0.014)	(0.010)	(0.009)	(0.023)	(0.007)
Small Storm	-0.012	-0.013**	-0.012**	-0.002	0.002	-0.001
	(0.009)	(0.007)	(0.005)	(0.004)	(0.008)	(0.004)
Denominator	Adults	Earners	Earned Hours	Earners	Jobs	Adults
Observations	20,808	20,808	20,808	20,808	20,808	20,808
R-squared	0.073	0.131	0.146	0.068	0.024	0.016

Results from weighted municipal*quarter regressions. The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). Regressions control for municipal fixed effects, time fixed effects as well as the share of the working age population in each education category, the share of women in the working age population, the number of men, the number of women, the number men age 15-30 and the number of women age 15-30. The sample is restricted to municipalities outside of Mindanao. The standard errors (in parentheses) account for potential correlation within province. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.42: Individual-level results: Impacts on wages and employment [Table 5] – Alternative Paramaterization

	(1)	(2)	(3)	(4)
Panel A: Impact on Employment per Adult				
	employed	employed	employed	employed
Big Storm	0.014*	-0.005	-0.005	-0.007*
	(0.008)	(0.004)	(0.004)	(0.004)
Small Storm	-0.012***	-0.001	-0.001	0.000
	(0.004)	(0.002)	(0.002)	(0.002)
Observations	3,402,456	3,402,456	3,402,456	2,464,172
R-squared	0.000	0.023	0.228	0.219
Mean Dep. Var	0.600	0.600	0.600	0.600
Panel B: Impact on Log of Wages				
	wage/ week	wage/ week	wage/ week	wage/ week
Big Storm	-0.246***	-0.022*	-0.024**	-0.027**
	(0.044)	(0.013)	(0.011)	(0.011)
Small Storm	0.105***	-0.005	-0.007	-0.010**
	(0.019)	(0.006)	(0.005)	(0.005)
Observations	860,809	860,809	860,809	660,650
R-squared	0.012	0.216	0.444	0.446
Mean Dep. Var	6.900	6.900	6.900	7.000
Time FE	Yes	Yes	Yes	Yes
Mun FE	No	Yes	Yes	Yes
Ind Contr	No	No	Yes	Yes
Mindanao Incl.	Yes	Yes	Yes	No

Notes: Results from weighted individual regressions. The dependent variable is a dummy equal to one if the individual is employed (Panel A) and log of wages for employed individuals (Panel B). Regressions control for time fixed effects (Column 1-4), municipal fixed effects (Column 2-4), as well as the respondent's age, age square, education levels and gender (Column 3-4). In Column 4, the sample is restricted to municipalities outside of Mindanao. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.43: Individual-level results: decomposition [Table 6] – Alternative Paramaterization

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact on Intensive Margins (Earnings and Hours)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.027**	-0.018**	-0.016*	-0.011	-0.015**	-0.002
	(0.011)	(0.009)	(0.009)	(0.008)	(0.007)	(0.004)
Small Storm	-0.010**	-0.008**	-0.003	-0.007*	-0.001	-0.002
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	660,650	1,430,357	660,650	660,650	660,650	660,650
R-squared	0.446	0.128	0.094	0.417	0.093	0.039
Panel B: Impact on Extensive Margins						
	employed	job	wage missing	wage observed	zero hours	lost job quarter
Big Storm	-0.007*	-0.006	0.006	-0.006*	0.001	0.001
	(0.004)	(0.004)	(0.006)	(0.004)	(0.001)	(0.002)
Small Storm	0.000	0.000	-0.001	0.000	0.000	-0.002**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)
Sample	All	All	Earners	All	All	All
Observations	2,464,172	2,464,172	1,430,353	2,464,172	2,464,172	2,464,172
R-squared	0.219	0.228	0.188	0.097	0.015	0.021
Mean Dep. Var	0.573	0.581	0.507	0.286	0.009	0.030

Notes: Results from weighted individual regressions. In Panel A, the dependent variable is the log weekly wage for employed individuals (Column 1), number of hours worked for employed individuals (Column 2), number of hours worked for employed individuals earning a wage (Column 3), hourly wage for employed individuals (Column 4), number of days worked for employed individuals earning a wage (Column 5), number of hours worked per day for employed individuals earning a wage (Column 6). In Panel B, the dependent variables are a series of dummies equal to one if: the individual is employed (Column 1), the individual has a job (Column 2), the individual is employed but their wage is not observed (Column 3), the individual reports a wage regardless of employment status (Column 4), the individual reports having a job but working zero hours in the last 7 days (Column 5), the individual reports not having a job now, but having worked in the last 3 months (Column 6). Regressions control for municipal fixed effects, time fixed effects as well as respondent's age, age square, education levels and gender. The standard errors (in parentheses) account for potential correlation within municipality. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.44: Aggregate-level results - Persistence [Table 7] – Alternative Paramaterization

	(1) inc/ adult	(2) wage/ week	(3) wage/ hour	(4) hours/ earner	(5) earners/ job	(6) job/ adult
Big Storm						
current	-0.079***	-0.036**	-0.023**	-0.014	-0.029	-0.013**
	(0.026)	(0.015)	(0.011)	(0.010)	(0.025)	(0.006)
lag 1	-0.030	-0.017	-0.005	-0.011	-0.006	-0.007
	(0.026)	(0.015)	(0.014)	(0.011)	(0.027)	(0.006)
lag 2	0.036	0.017	-0.002	0.019*	0.026	-0.008
	(0.026)	(0.013)	(0.011)	(0.011)	(0.022)	(0.006)
lag 3	-0.036	-0.007	-0.007	-0.001	-0.012	-0.016**
	(0.022)	(0.012)	(0.013)	(0.011)	(0.022)	(0.007)
Small Storm (lags estimated but not displayed)						
current	-0.014	-0.014**	-0.013***	-0.001	0.001	-0.001
	(0.009)	(0.006)	(0.005)	(0.004)	(0.007)	(0.004)
Observations	20,579	20,579	20,579	20,579	20,602	20,835
R-squared	0.074	0.131	0.144	0.068	0.025	0.017

Notes: Results from weighted municipal*quarter regressions.The dependent variable is the average income from employment per adult (Column 1), the average income from employment for employed individuals (Column 2), the average hourly wage for employed individuals (Column 3), the average number of hours worked for employed individuals (Column 4), the proportion of individuals who had jobs who reported a salary (Column 5), the proportion of adults who had jobs (Column 6). Regressions control for municipal fixed effects, time fixed effects as well as the share of the working age population in each education category, the share of women in the working age population, the number of men, the number of women, the number men age 15-30 and the number of women age 15-30. The sample is restricted to municipalities outside of Mindanao. The standard errors (in parentheses) account for potential correlation within province. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.45: Individual-level results: A closer look at the private sector [Table 8] – Alternative Paramaterization

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Decomposition of Impacts among Private Sector Wage Employment and Other Jobs						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	0.002	-0.031***	-0.021	0.020	-0.031**	0.010*
	(0.019)	(0.011)	(0.014)	(0.013)	(0.013)	(0.006)
Small Storm	-0.017*	-0.003	-0.003	-0.013*	-0.002	-0.001
	(0.009)	(0.006)	(0.006)	(0.008)	(0.005)	(0.003)
Big Storm * priv	-0.049**	0.055***	0.010	-0.056***	0.028**	-0.019***
	(0.024)	(0.017)	(0.016)	(0.019)	(0.014)	(0.007)
Small Storm * priv	0.014	-0.017*	-0.001	0.013	0.001	-0.002
	(0.011)	(0.009)	(0.007)	(0.010)	(0.006)	(0.004)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	660,650	1,430,357	660,650	669,711	660,650	660,650
R-squared	0.469	0.156	0.124	0.441	0.119	0.051
Panel B: Decomposition of Impacts among Permanent and Temporary Private Sector Wage Jobs						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm * permanent	-0.024**	0.003	0.003	-0.027**	0.003	-0.001
	(0.012)	(0.010)	(0.010)	(0.012)	(0.007)	(0.005)
Small Storm * permanent	-0.009	0.000	0.003	-0.012**	0.002	0.001
	(0.006)	(0.004)	(0.004)	(0.006)	(0.003)	(0.003)
Big Storm * temporary	-0.037	-0.064***	-0.057***	0.019	-0.044***	-0.013
	(0.023)	(0.019)	(0.020)	(0.017)	(0.014)	(0.010)
Small Storm * temporary	0.005	-0.012	-0.010	0.014	-0.003	-0.007
	(0.011)	(0.010)	(0.010)	(0.010)	(0.007)	(0.006)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	465,245	510,571	465,245	465,245	465,245	465,245
R-squared	0.418	0.088	0.089	0.395	0.081	0.045
Equality F-stat	0.261	9.617	6.986	5.343	8.613	1.221
Equality p-val	0.610	0.002	0.008	0.021	0.003	0.269

Notes: Results from weighted individual regressions. In Panel A, the dependent variable is the log weekly wage for employed individuals (Column 1), number of hours worked for employed individuals (Column 2), number of hours worked for employed individuals earning a wage (Column 3), hourly wage for employed individuals (Column 4), number of days worked for employed individuals earning a wage (Column 5), number of hours worked per day for employed individuals earning a wage (Column 6). Regressions control for municipal fixed effects, time fixed effects as well as respondent's age, age square, education levels and gender. In Panel A regressions include a private sector dummy. In Panel B regressions include a permanent contract dummy. The standard errors (in parentheses) account for potential correlation within municipality. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.46: Panel-level results: decomposition [Table 9] – Alternative Paramaterization

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact on Earnings and Hours (All Employees)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.024**	-0.018**	-0.010	-0.019**	-0.004	-0.008*
	(0.010)	(0.009)	(0.008)	(0.008)	(0.006)	(0.004)
Small Storm	-0.007	-0.010**	-0.004	-0.005	0.000	-0.005**
	(0.006)	(0.005)	(0.004)	(0.005)	(0.004)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	267,038	699,704	277,932	267,038	277,928	277,928
R-squared	0.465	0.131	0.107	0.439	0.100	0.052
Panel B: Impact on Earnings and Hours (Same Job Type)						
	wage/ week	hours/ worker	hours/ earner	wage/ hour	days/ earner	hours/ day
Big Storm	-0.015	-0.016*	0.006	-0.021**	0.001	0.005
	(0.012)	(0.009)	(0.009)	(0.010)	(0.007)	(0.004)
Small Storm	0.002	-0.008*	0.003	-0.002	0.002	0.000
	(0.007)	(0.005)	(0.005)	(0.006)	(0.004)	(0.002)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	194,717	502,444	195,728	194,717	195,726	195,726
R-squared	0.491	0.146	0.124	0.462	0.121	0.054
Mun Fe	No	No	No	No	No	No

Notes: Results from weighted individual regressions. In Panel A, the dependent variable is the log weekly wage for employed individuals (Column 1), number of hours worked for employed individuals (Column 2), number of hours worked for employed individuals earning a wage (Column 3), hourly wage for employed individuals (Column 4), number of days worked for employed individuals earning a wage (Column 5), number of hours worked per day for employed individuals earning a wage (Column 6). In Panel B, the dependent variables are a series of dummies equal to one if: the individual is employed (Column 1), the individual has a job (Column 2), the individual is employed but their wage is not observed (Column 3), the individual reports a wage regardless of employment status (Column 4), the individual reports having a job but working zero hours in the last 7 days (Column 5), the individual reports not having a job now, but having worked in the last 3 months (Column 6). Regressions control for time fixed effects as well as municipal fixed effects (Panel A) and individual fixed effects (Panel B). In Panel A, regression control for the respondent's age, age square, education levels and gender. The standard errors (in parentheses) account for potential correlation within municipality. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.47: Individual results: Impacts on composition of the sample

	(1) Female	(2) Age	(3) No Schooling	(4) Some Primary	(5) Primary Graduate	(6) Some High School	(7) High School Graduate	(8) Some College
Panel A: Impact on the Characterizistic (Composition) of the Full Sample								
Big Storm	0.001	0.021	0.000	-0.001	0.004*	0.002	-0.004	-0.001
	(0.002)	(0.094)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Small Storm	0.000	0.062	0.001*	0.000	0.001	-0.004***	0.000	0.003
	(0.001)	(0.047)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Observations	2,464,172	2,464,172	2,464,172	2,464,172	2,464,172	2,464,172	2,464,172	2,464,172
R-squared	0.002	0.010	0.023	0.080	0.038	0.008	0.032	0.072
Mean Dep. Var	0.510	36.070	0.010	0.130	0.150	0.160	0.260	0.280
Panel B: Impact on the Characterizistic (Composition) of the Employed Individuals								
Big Storm	0.002	0.229	0.000	-0.003	0.009**	0.002	-0.006	-0.002
	(0.005)	(0.150)	(0.001)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Small Storm	0.004	0.125*	0.000	-0.001	0.001	-0.003*	-0.001	0.004
	(0.003)	(0.071)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Observations	669,711	669,711	669,711	669,711	669,711	669,711	669,711	669,711
R-squared	0.017	0.015	0.024	0.094	0.046	0.012	0.035	0.075
Mean Dep. Var	0.400	33.920	0.010	0.100	0.130	0.120	0.290	0.360
Panel C: Impact on the Characterizistic (Composition) of the Individuals Earning a Wage								
Big Storm	0.002	0.229	0.000	-0.003	0.009**	0.002	-0.006	-0.002
	(0.005)	(0.150)	(0.001)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Small Storm	0.004	0.125*	0.000	-0.001	0.001	-0.003*	-0.001	0.004
	(0.003)	(0.071)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Observations	669,711	669,711	669,711	669,711	669,711	669,711	669,711	669,711
R-squared	0.017	0.015	0.024	0.094	0.046	0.012	0.035	0.075
Mean Dep. Var	0.400	33.920	0.010	0.100	0.130	0.120	0.290	0.360

Notes: Results from weighted individual regressions. The sample is restricted to individual employed (Panel B) and individuals observed earning a wage (Panel C) . The dependent variable is a dummy variable equal to one if the respondent is female (Column 1), respondent age (Column 2), a dummy variable if the respondent did not complete any grade (Column 3), attended, but did not graduate from, primary school (Column 4), graduated from primary school but did not attend high school (Column 5), attended, but did not graduate from, high school (Column 6) graduated from high school but did not attend college (Column 7), attended College (Column 8). Regressions control for municipal fixed effects, region-specified time fixed effects. The standard errors (in parentheses) account for potential correlation within province. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.48: Individual results: Impacts on composition of the sample [Table A.47] – Alternative Paramaterization

	(1) Female	(2) Age	(3) No Schooling	(4) Some Primary	(5) Primary Graduate	(6) Some High School	(7) High School Graduate	(8) Some College
Panel A: Impact on the Characteriristic (Composition) of the Full Sample								
Big Storm	0.001	0.102	-0.001	-0.001	0.003	0.004	-0.003	-0.003
	(0.002)	(0.113)	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Small Storm	0.001	0.084*	0.001	0.000	0.001	-0.003**	0.001	0.001
	(0.001)	(0.049)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Observations	2,464,172	2,464,172	2,464,172	2,464,172	2,464,172	2,464,172	2,464,172	2,464,172
R-squared	0.002	0.010	0.023	0.080	0.038	0.008	0.032	0.072
Mean Dep. Var	0.510	36.070	0.010	0.130	0.150	0.160	0.260	0.280
Panel B: Impact on the Characteriristic (Composition) of the Individuals Employed								
Big Storm	0.002	0.150	-0.000	-0.002	0.006	0.005	-0.009**	-0.001
	(0.003)	(0.125)	(0.001)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Small Storm	0.004**	0.031	0.000	-0.000	0.001	-0.003**	0.001	0.002
	(0.002)	(0.054)	(0.000)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Observations	1,453,619	1,453,619	1,453,619	1,453,619	1,453,619	1,453,619	1,453,619	1,453,619
R-squared	0.013	0.016	0.041	0.106	0.048	0.010	0.043	0.091
Mean Dep. Var	0.39	37.66	0.01	0.15	0.17	0.13	0.27	0.28
Panel C: Impact on the Characteriristic (Composition) of the Individuals Earning a Wage								
Big Storm	0.009	0.431**	0.000	-0.002	0.007	0.008	-0.013**	0.000
	(0.006)	(0.178)	(0.001)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
Small Storm	0.006**	0.091	-0.000	-0.001	-0.000	-0.003	0.002	0.002
	(0.003)	(0.076)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Observations	669,711	669,711	669,711	669,711	669,711	669,711	669,711	669,711
R-squared	0.017	0.015	0.024	0.094	0.046	0.012	0.035	0.075
Mean Dep. Var	0.51	36.07	0.01	0.13	0.15	0.16	0.26	0.28

Notes: Results from weighted individual regressions. The sample is restricted to individual employed (Panel B) and individuals observed earning a wage (Panel C) . The dependent variable is a dummy variable equal to one if the respondent is female (Column 1), respondent age (Column 2), a dummy variable if the respondent did not complete any grade (Column 3), attended, but did not graduate from, primary school (Column 4), graduated from primary school but did not attend high school (Column 5), attended, but did not graduate from, high school (Column 6) graduated from high school but did not attend college (Column 7), attended College (Column 8). Regressions control for municipal fixed effects, region-specified time fixed effects. The standard errors (in parentheses) account for potential correlation within province. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.49: Individual-level results: Employment in different types of jobs

	(1)	(2)	(3)	(4)	(5)	(6)
	Self-	Private Sector		Farming		
	Employed	Permanent	Temporay	Own	Wage	Government
Panel A: Total Effect (Unconditional on having a job)						
Big Storm	-0.002	0.001	-0.001	0.000	-0.001	-0.002**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)
Small Storm	0.000	-0.001	0.001	0.003*	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2,464,172	2,464,172	2,464,172	2,464,172	2,464,172	2,464,172
R-squared	0.056	0.092	0.028	0.247	0.115	0.073
Mean Dep. Var	0.131	0.169	0.057	0.127	0.046	0.043
Panel B: Composition Effect (Conditional on having a job)						
Big Storm	-0.002	0.004	-0.001	0.003	-0.002	-0.004**
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)
Small Storm	-0.002	-0.001	0.001	0.003*	0.000	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Observations	1,453,619	1,453,619	1,453,619	1,453,619	1,453,619	1,453,619
R-squared	0.084	0.170	0.065	0.315	0.160	0.113
Mean Dep. Var	0.226	0.291	0.097	0.218	0.078	0.074
Panel C: Composition Effect (Conditional on earning a wage)						
Big Storm	0.000	0.007	0.003	0.000	-0.001	-0.010***
	(0.001)	(0.008)	(0.007)	(0.001)	(0.006)	(0.004)
Small Storm	0.000	-0.006	0.004	0.000	0.004	-0.002
	(0.001)	(0.005)	(0.005)	(0.000)	(0.003)	(0.002)
Observations	669,711	669,711	669,711	669,711	669,711	669,711
R-squared	0.005	0.145	0.073	0.023	0.366	0.210
Mean Dep. Var	0.005	0.540	0.183	0.001	0.132	0.127

Notes: Results from weighted individual regressions. The dependent variable is a dummy equal to one if the individual is: self-employed (Column 1), has a permanent job in the private sector (Column 2), has a temporary job in the private sector (Column 3), works on the family farm (Column 4), works for a wage on someone's else farm (Column 5), is employed in the public sector (Column 6). Regressions control for municipal fixed effects, time fixed effects as well as respondent's age, age square, education levels and gender. The standard errors (in parentheses) account for potential correlation within municipality. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.50: Individual-level results: Employment in different types of jobs [table A.49] – Alternative Paramaterization

	(1)	(2)	(3)	(4)	(5)	(6)
	Self-	Private Sector		Farming		
	Employed	Permanent	Temporay	Own	Wage	Government
Panel A: Total Effect (Unconditional on having a job)						
Big Storm	-0.005**	-0.001	-0.001	0.001	0.001	-0.002
	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)	(0.001)
Small Storm	0.000	-0.002	0.001	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2,464,172	2,464,172	2,464,172	2,464,172	2,464,172	2,464,172
R-squared	0.056	0.092	0.028	0.247	0.115	0.073
Mean Dep. Var	0.131	0.169	0.057	0.127	0.046	0.043
Panel B: Composition Effect (Conditional on having a job)						
Big Storm	-0.006	0.002	-0.001	0.004	0.000	-0.002
	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.002)
Small Storm	-0.001	-0.002	0.002	0.001	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Observations	1,453,619	1,453,619	1,453,619	1,453,619	1,453,619	1,453,619
R-squared	0.084	0.170	0.065	0.315	0.160	0.113
Mean Dep. Var	0.226	0.291	0.097	0.217	0.078	0.079
Panel C: Composition Effect (Conditional on earning a wage)						
Big Storm	0.001	-0.000	0.005	-0.001	0.004	-0.009**
	(0.001)	(0.009)	(0.007)	(0.001)	(0.006)	(0.004)
Small Storm	-0.000	-0.008*	0.006	0.001	0.002	-0.001
	(0.001)	(0.004)	(0.004)	(0.000)	(0.003)	(0.002)
Observations	669,711	669,711	669,711	669,711	669,711	669,711
R-squared	0.005	0.145	0.073	0.023	0.366	0.210
Mean Dep. Var	.005	.54	.183	.001	.132	.127

Notes: Results from weighted individual regressions. The dependent variable is a dummy equal to one if the individual is: self-employed (Column 1), has a permanent job in the private sector (Column 2), has a temporary job in the private sector (Column 3), works on the family farm (Column 4), works for a wage on someone's else farm (Column 5), is employed in the public sector (Column 6). Regressions control for municipal fixed effects, time fixed effects as well as respondent's age, age square, education levels and gender. The standard errors (in parentheses) account for potential correlation within municipality. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.51: Individual-level and panel-level results: Labour supply

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full Individual Dataset						
	in labour force	searched work	in lf no work	in lf searched	wants more work	searched for more work
Big Storm	-0.004	0.002	0.004	0.001	0.003	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.005)
Small Storm	0.003*	-0.003	0.002	0.000	-0.008	-0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.003)
Observations	2,464,172	2,464,172	1,588,750	1,010,552	1,430,353	1,098,598
R-squared	0.233	0.043	0.060	0.063	0.114	0.104
Mean Dep. Var	0.640	0.071	0.106	0.066	0.184	0.093
Panel B: Panel Dataset						
	in labour force	searched work	in lf no work	in lf searched	wants more work	searched for more work
Big Storm	-0.002	0.002	-0.002	-0.002	-0.007	0.001
	(0.004)	(0.003)	(0.004)	(0.003)	(0.008)	(0.006)
Small Storm	0.001	-0.004*	0.000	-0.001	0.006	0.008**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.003)
Observations	1,294,842	1,294,842	1,294,842	399,704	699,704	455,862
R-squared	0.001	0.002	0.002	0.001	0.005	0.016
Mean Dep. Var	0.665	0.070	0.603	0.047	1.808	1.900

Notes: Results from weighted individual regressions. The dependent variable is a dummy equal to one if the individual is:in the labor force (Column 1) report having searched for work in the past week, regardless of labour force status (Column 2), not working, conditional on being in the labour force (Column 3), looking for work, conditional on being in the labour force and not working (Column 4), wanting more work, conditional on already having a job (Column 5), reported looking for additional work, conditional already having a job (Column 6). Regressions control for municipal fixed effects, time fixed effects as well as respondent's age, age square, education levels and gender. The standard errors (in parentheses) account for potential correlation within municipality. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.52: Individual-level and panel-level results: Labour supply [Table A.51] – Alternative Paramaterization

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full Individual Dataset						
	in labour force	searched work	in lf no work	in lf searched	wants more work	searched for more work
Big Storm	-0.005	0.002	0.004	-0.002	0.002	0.001
	(0.004)	(0.003)	(0.004)	(0.003)	(0.009)	(0.006)
Small Storm	0.002	-0.004**	0.003*	-0.001	-0.007	-0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.003)
Observations	2,464,172	2,464,172	1,588,750	1,010,552	1,430,353	1,098,598
R-squared	0.233	0.043	0.060	0.063	0.114	0.104
Mean Dep. Var	0.640	0.071	0.106	0.066	0.184	0.093
Panel B: Panel Dataset						
	in labour force	searched work	in lf no work	in lf searched	wants more work	searched for more work
Big Storm	-0.003	-0.001	-0.005	-0.003	-0.008	0.005
	(0.004)	(0.004)	(0.004)	(0.003)	(0.010)	(0.008)
Small Storm	-0.001	-0.004*	0.001	-0.002	0.007	0.007**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.004)
Observations	1,294,842	1,294,842	1,294,842	399,704	699,704	455,862
R-squared	0.001	0.002	0.002	0.001	0.005	0.016
Mean Dep. Var	0.665	0.070	0.603	0.047	1.808	1.900

Notes: Results from weighted individual regressions. The dependent variable is a dummy equal to one if the individual is:in the labor force (Column 1) report having searched for work in the past week, regardless of labour force status (Column 2), not working, conditional on being in the labour force (Column 3), looking for work, conditional on being in the labour force and not working (Column 4), wanting more work, conditional on already having a job (Column 5), reported looking for additional work, conditional already having a job (Column 6). Regressions control for municipal fixed effects, time fixed effects as well as respondent's age, age square, education levels and gender. The standard errors (in parentheses) account for potential correlation within municipality. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.53: Individuals-level results: Heterogenous treatment effects by managerial and non-managerial private sector jobs)[Table A.37] – Alternative Paramaterization

	(1) wage/ week	(2) hours/ worker	(3) hours/ earner	(4) wage/ hour	(5) days/ earner	(6) hours/ day
Big Storm * non manag	-0.035***	-0.035***	-0.021**	-0.017*	-0.019**	-0.003
	(0.013)	(0.010)	(0.010)	(0.009)	(0.009)	(0.005)
Small Storm * non manag	-0.011*	-0.011**	-0.005	-0.006	-0.002	-0.003
	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
Big Storm * manag	0.199**	0.141***	0.176***	0.008	0.092***	0.081***
	(0.085)	(0.021)	(0.037)	(0.094)	(0.021)	(0.024)
Small Storm * manag	-0.026	0.004	-0.011	-0.017	-0.019	0.008
	(0.033)	(0.012)	(0.020)	(0.032)	(0.014)	(0.012)
Sample	Earners	All	Earners	Earners	Earners	Earners
Observations	566,279	1,317,287	566,279	575,322	566,279	566,279
R-squared	0.464	0.157	0.101	0.414	0.101	0.045
Equality F-stat	7.148	56.877	25.197	0.067	21.428	11.371
Equality p-val	0.008	0.000	0.000	0.795	0.000	0.001

Notes: Results from weighted individual regressions. Sample is restricted to individuals working in the private sector. In Panel A, the dependent variable is the log weekly wage for employed individuals (Column 1), number of hours worked for employed individuals (Column 2), number of hours worked for employed individuals earning a wage (Column 3), hourly wage for employed individuals (Column 4), number of days worked for employed individuals earning a wage (Column 5), number of hours worked per day for employed individuals earning a wage (Column 6). Regressions control for municipal fixed effects, region-specified time fixed effects as well as respondent's age, age square, education levels and gender. Regression also include a full set of job type dummies. The standard errors (in parentheses) account for potential correlation within province. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Table A.54: Main storms data

		Official Storm Records					Storm Model with different parameters Municipalities with super-typhoon windspeeds							
Storm Name	Year	Speed (km/h)	Press. hPa	Damage ($mill)	Deaths	SS Cat	b=1.8 r=20	b=2 r=20	b=2 r=25	b=2 r=30	b=2.2 r=20	b=2.2 r=25	b=2.4 r=30	Max Wind
Imbudo (Harurot)	2003	165	935	$383	85	4	86	96	108	125	99	117	135	130
Nida (Dindo)	2004	175	935	$1.3	31	5	11	11	14	20	11	16	21	145
Conson (Frank)	2004	150	960	$3.8	30	3	0	0	0	0	0	0	0	26
Mindulle (Igme)	2004	175	940	$833	56	4	1	1	1	1	1	1	1	126
Muifa (Unding)	2004	150	950	$18	108	4	0	0	0	1	26	9	43	114
Nanmadol (Yoyong)	2004	165	935	$60.8	77	4	69	77	90	108	83	97	116	131
Xangsane (Milenyo)	2000	155	940	$750	312	4	71	88	99	110	93	105	157	140
Cimaron (Paeng)	2006	185	920	$31	34	5	88	90	106	121	92	109	123	158
Chebi (Queenie)	2006	195	925	Unknown	1	4	87	94	97	115	96	100	124	149
Durian (Reming)	2006	195	915	$530	1500	4	79	89	101	121	93	107	142	140
Utor (Seniang)	2001	155	945	$15.8	38	3	13	18	20	30	28	32	66	126
Fengshen (Frank)	2008	165	945	$430	1,371	3	35	66	66	83	94	104	165	136
Nuri (Karen)	2008	140	955	$85	20	3	2	2	6	9	2	7	11	123
Hagupit (Nina)	2008	165	935	$3 billion	67	4	1	1	1	1	1	1	1	121
Parma (Pepeng)	2009	185	930	$617	500	4	0	0	0	0	23	4	32	114
Summary: Total Super Typhoons Registered by Parameterization							12	12	12	13	14	14	14	
Selected Small storms mismeasured by certain Parameterizations														
Krovanh (NiÃśa)	2003	165	970	$0.073	4	2	0	0	0	0	0	0	15	108
Lekima (Labuyo)	2001	130	965	Unknown	*	2	0	0	0	0	5	0	6	111
Linfa (Chedeng)	2003	110	980	$1.25	41	n/a	0	0	0	0	0	0	0	92

Figure A.1: Small and Big Storm Incidence by Year and Quarter: Percentage of Municipalities hit

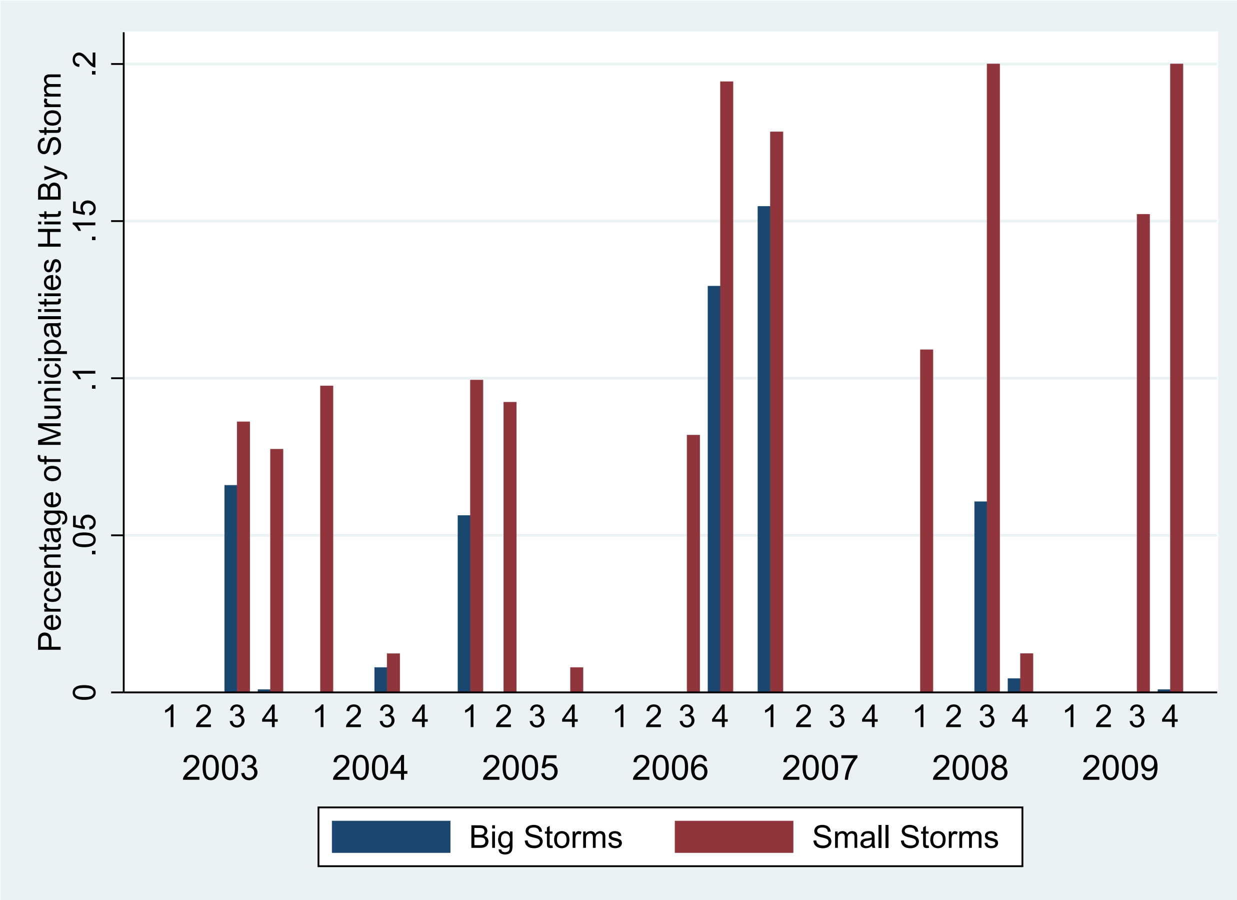

Figure A.2: Storm damage by municipality (Sept-Dec 2006)