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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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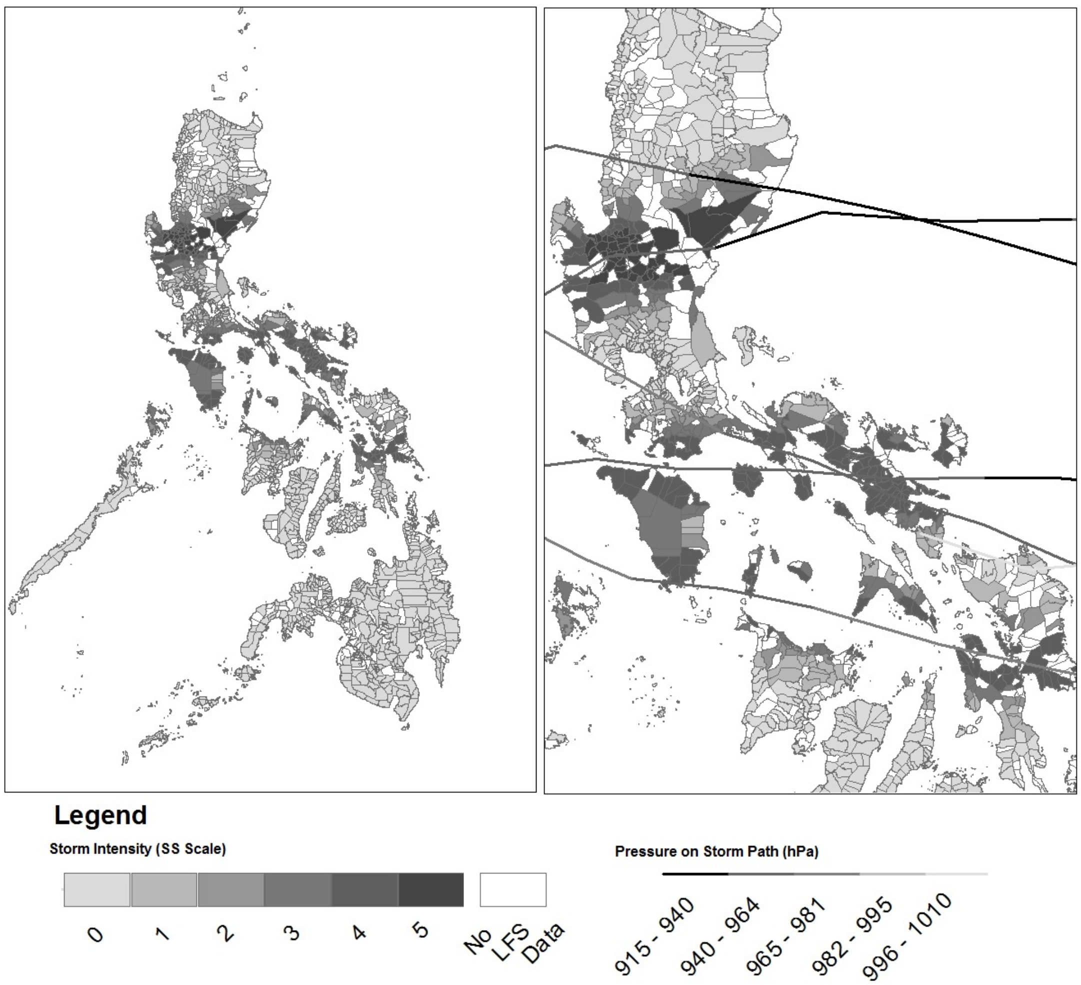
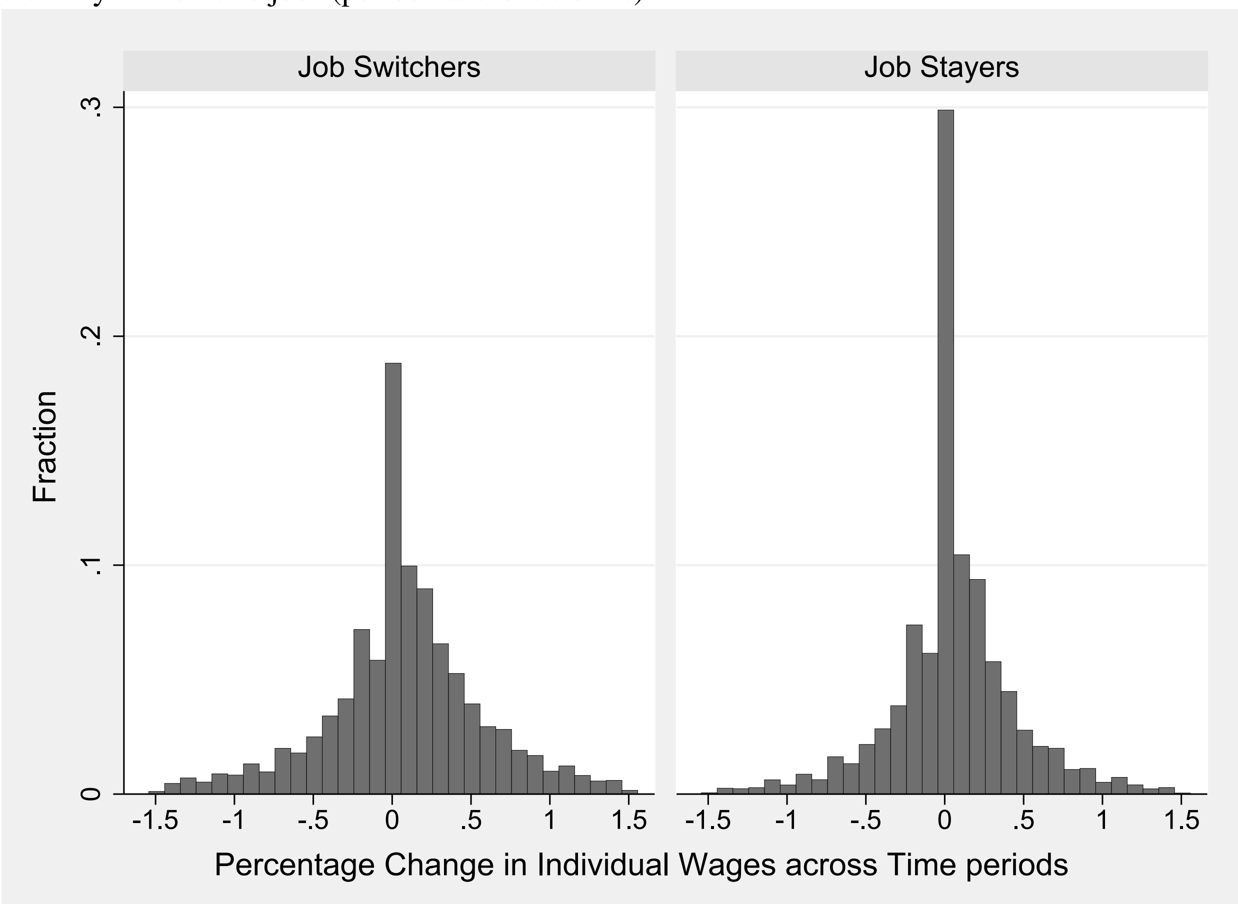
Figures

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.