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 typhoons have short-run negative effects on income but no effect on employment levels. We find clear evidence of downward flexibility of hours worked and hourly wages. We rule out the possibility that the results are due to migration, or other changes to labour supply or sample composition. These results are strongest for formal, wage-paying jobs, suggesting that downward flexibility is built into long-term employment agreements.

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1 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 large negative welfare consequences, especially in developing countries, where social safety nets are less likely to be in place. The extent to which labour markets are able to adjust to shocks - particularly large environmental shocks, which are becoming increasingly common worldwide - 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. This panel of 1.8 million observations allows us to observe the same individuals, who have not migrated or dropped out of the sample, in both periods when shocks hit and those that don’t, to study the impacts on their wages and employment. 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 take advantage of 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 per cent reduction in per capita wage income. This impact on incomes appears to be driven by both a reduction in the average number of hours worked per worker and a reduction in 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 out have an impact on the marginal revenue product of labour, including destruction of capital and infrastructure, or a decline in prices due to disruptions to trade or local consumer demand. We do not take a stance on which of those channels is driving the economic shocks we see in the data: 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 impacts 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 confirm the existence of downward nominal wage flexibility at the worker level by ruling out channels related to changes in sample, workforce or sectoral composition. Our main concern is that migration may have altered the composition of the workforce for whom we observe wages in typhoon-quarters, which could be driving the reduction in wages.\(^2\) We 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

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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 Typhoons may very well have induced out migration (Kleemans and Magruder, 2012; Gröger and Zylberberg, 2015). This could include international migration, which is common in this context (Theoharides, 2014).
report a wage. Most importantly we study our panel of individuals that we observe in employment in at least two periods. 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 in employment contracts. It is important to note that this panel sample is restricted to individuals who did not migrate as a result of the shock.

Fourth, we explore the mechanisms behind the effects. 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.

To explain wage flexibility in long-term contracts we develop an implicit contract model (Azariadis, 1975; Baily, 1974; Rosen, 1985; Miyazaki and Neary, 1985). Firms and workers engage in risk sharing in the event of large demand shocks. Workers 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. Optimal contracts can adjust to large shocks through lay-offs or work sharing (reductions in hours per worker). Firms will rely more on the latter when workers are more risk averse or face worse outside options, or when labour is relatively divisible (Mortensen, 1978).\footnote{In other words, the marginal productivity of the number of hours used in production is equal to the marginal productivity of increasing the number of employees. When labour is indivisible, it is more costly for firms to cut hours than it is for them to lay off workers.} Under certain conditions, even when labour is relatively indivisible, no lay-offs occur. We argue that it is plausible that these conditions could hold in the context of the Philippine labour market.

Finally, we find some evidence that managers experience a sizeable increase in their weekly wages that appears to be driven by a large increase in the number of hours worked. This suggests a skill bias of the impact of large economic shocks. 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.

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 use plausibly exogenous shocks to identify changes in the labour market (Kaur, 2014; Holzer and Montgomery, 1993). 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

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.⁶

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⁴Our 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 hit regularly 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).

⁵Keane 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.

⁶We think this is a setting in which risk-sharing contracts are particularly feasible: since storms are easily observed and verified by both sides of the market, they should be easy to implicitly contract upon. This could happen through long-established norms about how employers and employees expect each other to react when
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). 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 pay checks in the absence of unemployment insurance or good alternatives.

The remainder of the paper is organized as follows. Section 2 discusses the context and data. Section 3 establishes that shocks have large but temporary negative effects on labour markets. Section 4 presents evidence of substantial downward nominal wage flexibility. Section 5 explores the mechanisms behind these findings. In Section 6 we develop a model to explain why wages and hours fall, but employment does not. Section 7 concludes.

## 2 Context and data

In this section we describe the context and argue that the Philippines is an ideal setting for our analysis. Typhoons are a regular occurrence in the Philippines, and generate large welfare costs (Anttila-Hughes and Hsiang, 2013; Bankoff, 2002; Ugaz and Zanolini, 2011).

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

8 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).
2.1 Typhoons in the Philippines

We leverage data from the Japan Meteorological Agency Tropical Cyclone Database to generate measures of storm exposure at the municipal-quarter level. The database provides information on each tropical storm passing through the North-West Pacific Ocean from 2000 to 2010.\textsuperscript{9} The data take 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 involves three main steps. First, for each storm, we compute the maximum wind speed that affected the municipality. 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 apply a model of wind-speed decay from the centre of the storm to estimate wind speeds for each municipality–storm combination (Holland, 1980).\textsuperscript{10} The model uses distance from the eye of storm and the pressure at the eye to calculate a wind speed at any point.

[FIGURE 1 HERE.]

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. For instance, we have surveys from October for every year from 2003 to 2009. If a storm passed through during the months of August, September or October, it would be assigned to the time period in the Labor Force Survey (LFS) data corresponding to the survey taken in October that year.

[TABLE 1 HERE.]

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

\textsuperscript{9}These data can be accessed online at http://www.jma.go.jp/en/typh/, last accessed on 1 December 2012.

\textsuperscript{10}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).
municipality was exposed to. 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 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.\textsuperscript{11} 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’.

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. The biggest wind speed experienced was 143 knots. On average, 18.6 per cent of the quarterly municipality observations are affected by a tropical storm, but 39.2 per cent of those are too small to be classified on the Saffir-Simpson scale. Across the country, 23 of the 26 quarters for which we have employment data experienced storms. Twenty quarters experienced storms that registered on the Saffir-Simpson scale, and eight of those quarters were classified as catastrophically damaging (scale 4 & 5). Less than 2 per cent of our quarterly municipal observations reported very large storms (Saffir-Simpson classification 4 or 5).

The most active typhoon season in the sample period was September-December 2006. The variation in damage across municipalities during this period is revealing. This is not the season of the largest storm recorded during the study period, but damage is fairly widespread due to a number of storms: 18 per cent of municipalities experienced catastrophic damage, and 30 per cent had some experience of typhoons. The geographical variability is plotted on the maps below; the municipalities are coloured according to the Saffir-Simpson score of the biggest storm passing through during the quarter. Figure 1 (left panel) gives some impression of the damage across the entire country. Few storms passed through the South during this period, although storms did in other years. The right panel in Figure 1 plots the five typhoons that passed through that area during this period: darker red storms indicate lower pressure.

\textsuperscript{11}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.
cells. 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.\textsuperscript{12} Storm Durian is reported to have killed an estimated 720 people in the Philippines.

2.2 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.\textsuperscript{13} Data from the surveys are used to compute official employment statistics. 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. The NSO used the same sampling frame over the period, so to minimise sampling error across years, common samples were used in consecutive years. As a result, a number of households were interviewed more than once. We have access to the household IDs, which allows us to track households over time. We then use information on gender, age and education level to build a panel of individuals.

A person is considered employed if s/he reported to work 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. 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, and we compute

\textsuperscript{12}Our data contain names from the Japan Meteorological Agency Tropical Cyclone Database. The Philippine Atmospheric, Geophysical and Astronomical Services Administration names the storms.

\textsuperscript{13}More information on the survey design is available at: http://www.census.gov.ph/data/technotes/notelfs_new.html visited on 26 March 2012.
the employment ratio as a share of the working-age population rather than as a share of the economically active population.

To isolate differential treatment effects by employment type, our analyses use a basic typology of the jobs available in the Philippine labour market. These are:

**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.\(^\text{14}\)

**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.

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

\(^{14}\)According to the Republic of the Philippines Government Procurement Policy Board, ‘Pakyaw refers to a system of hiring a labor group for the performance of a specific work and/or service incidental to the implementation of an infrastructure project by administration whereby tools and materials are furnished by the implementing agency. For the specific work/service output, a lump-sum payment is made either through the group leader or divided among the *pakyaw* workers and disbursed using a payroll system’ (GPPB Resolution No. 18-2006, 6 December 2006).
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 quarter-on-quarter percentage wage changes for wage-earning individuals in all periods (not just when storms 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. However, individuals staying at the same jobs seem to exhibit downward flexibility in nominal wages. Large drops in the nominal wage are common.

3 Aggregate effects

In this section we establish that typhoons act as a strong (but temporary) labour demand shock. In the next section, we provide evidence on the channels through which the adjustment takes place.

3.1 Short-term effects

We start by estimating equations of the form:

\[ Y_{mpt} = \alpha S_{mpt} + \beta X_{mpt} + u_{mpt} + v_t + w_{mpt} \] (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. Given that we expect standard errors to be correlated for municipalities in the same provinces, standard errors are clustered at the provincial level.\textsuperscript{15}

\begin{table}
\caption{Table 3 Here.}
\end{table}

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). 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 $\alpha$.

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.

\begin{table}
\caption{Table 4 Here.}
\end{table}

We now decompose the effects on average income and estimate Equation (1) for a num-

\textsuperscript{15}The sample includes data from more than 80 provinces, so we are not concerned about bias in our standard errors as a result of having too few clusters (Cameron et al., 2008).
ber of other outcomes of interest using the specification with municipal fixed effects, time dummies and quarter-specific municipal controls on the non-Mindanao sample (Table 4).\textsuperscript{16} We find that the overall effect comes from a 2 per cent decline in hourly wage and a 1.5 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.

\[\text{[TABLE 5 HERE.]}\]

3.2 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 5, 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: it is more than 50 per cent lower for average wage and almost 80 per cent lower for average hourly wage. 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.

4 Downward nominal wage flexibility

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

\textsuperscript{16}Importantly, the results are robust to using alternative measures of storm strength (Tables A.1 and A.2).
and hourly wages. Consistent with our previous results, the effects on unemployment are very small. We show that the effects that we do find are driven entirely by the effects on self-employment. Employment in wage labour is not affected.

It is important to note that, as we are interested in total wages, our preferred measure is weekly wage income as this is the highest level of aggregation we can use. We can break it down into the number of hours worked and hourly wage. 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.

4.1 Individual decomposition

Consistent with the aggregate results discussed in the previous section, we estimate individual-level equations of the form:

\[ Y_{imt} = \alpha S_{mt} + \beta X_{imt} + u_m + v_t + w_{imt} \]  

(2)

Where \( Y_{imt} \) is the outcome of interest for individual \( i \) in municipality \( m \) 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 \( w_{imt} \) is the usual idiosyncratic term. Standard errors account for potential clustering of the errors 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 6 HERE.]

Individual-level results, available in Table 6, are consistent with the municipal-level results discussed above. Typhoons do not affect the probability of being employed, but

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

18We 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 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
average wages for employed individuals are 2.7 per cent lower in post-storm quarters. As before, the effects are no longer present after one quarter (Table A.3).

[TABLE 7 HERE.]

We can decompose the effect of typhoons on average income (Table 7). In the quarter after the storm, individuals report working 1.8 per cent fewer hours (Column 2). The point estimate on the hourly wages is negative and of the same order of magnitude as before. However, the individual-level measures are noisier than the aggregate measures used previously, and we are unable to reject the null of no effect.

The results discussed so far suggest that nominal wages exhibit significant downward flexibility when a typhoon hits. However, a well-established literature on the cyclicality of wages suggests that aggregation or selection effects could bias results either in favour of or against finding wage flexibility (Keane et al., 1988). For instance, if high-wage employees are more likely to be laid off during labour demand shocks, the results could be biased in favour of finding declines in real wages. If these high-productivity workers were replaced by lower-productivity workers, this would increase the extent of the bias and suggest no impact on overall employment. Conversely, if low-wage workers are laid off, this could lead to bias against finding a result of downward wage adjustment.

In the remainder of this section, we address each of those threats in turn and show that our results are robust. First, shocks could generate sectoral reallocation, which could reduce average wages without any wage adjustments for workers who do not switch jobs. Second, shocks could affect the sample composition. We start by showing that, based on average observable characteristics of individuals in the sample, employed individuals and individuals earning a wage are not affected by storms. We then use a panel of individuals – hereby

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on average wages in the aggregate data is 3.5 per cent, while the estimated effect on average wages in the individual data is 2.7 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 Table A.8. 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.
keeping the sample composition constant – and find that the results hold in this subsample. Finally, firms may have substituted highly paid skilled jobs for lower-skilled jobs to reduce their total wage costs. We restrict the sample to individuals who are employed in similar jobs during the period and find that the results hold for this subsample.

4.2 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.

[TABLE 8 HERE.]

Panel A of Table 8 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 less likely to be engaged in self-employment when storms hit. The main impact of storms on employment found in Table 7 is driven almost entirely by the impact on reduced self-employment, but these impacts are not likely to be driving our results on real wages. 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 allow no way to impute income from self-employment. This is an unfortunate limitation of the data. Anttila-Hughes and Hsiang (2013) use household data to show that storms have large impacts on household earnings, and that much of the effect comes through self-employment, but the focus of this paper is on wage employment. Wages are very rarely missing in private sector jobs (only about 9 per cent of the time). As we show in the sectoral analysis in Section 5, the impacts on income are driven by wage changes in the private sector.

Panel B of Table 8 shows that the composition of jobs across wage paying forms of employment (temporary or permanent private sector work, government work and wage-paying
farm labour) is unaffected by storms. Panel C of Table 8 reproduces the analysis on the sample of individuals earning a wage. We find that wage earners are very slightly less likely to work in the public sector. 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. It is important to 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.4).

4.3 Are the results driven by changes in sample composition?

Typhoons could affect the composition of the sample, which, depending on which individuals drop out of the sample, could generate the observed pattern of wage reduction. This could happen, for instance, through the channel of migration if certain types of individuals left the local area to look for work in areas less 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 9, 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 older and slightly less likely to have graduated from high school in the quarters in which storms hit.

[TABLE 9 HERE.]

4.4 Panel decomposition

We take advantage of the availability of panel data and show that the results are similar for this subsample. By construction, this set of analyses keeps the sample constant. 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. We estimate Equation (2) on the panel described in Section 3.2. Panel A of Table 10 shows the main results for the individual panel sample.\textsuperscript{19} Wages fall by 3.5 per cent, slightly more than the results from the individual data.\textsuperscript{20} Again, the results seem to be driven by a combination of a drop in hours per worker and a fall in the hourly wage: here the impact on hourly wages is larger and significant.

\[\text{[TABLE 10 HERE.]}\]

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) but further restrict the sample to individuals who stay in similar job types throughout the sample period.\textsuperscript{21} The results, available in Panel B of Table 10, confirm that even in this restricted sample workers experience a short-term drop in their wage income that is driven by a decline in both the hours worked and hourly wages.

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.9 confirm our earlier results.

Before exploring the mechanisms behind the estimated effects, 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 likely to hold in our case. Their argument is that if high-

\textsuperscript{19}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.5 in the Appendix).

\textsuperscript{20}Importantly, as in the full sample, there is no evidence that the probability of being employed is affected by the timing of typhoons (Column 1 of Table A.6).

\textsuperscript{21}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.
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.4). 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, panel data are used to overcome the possibility that storms change the sample selection, which might lead to our results being driven by churn in the labour market rather than actual falls in particular workers’ wages. While we cannot fully rule out the possibility that the panel members switched to lower-paid jobs within the same sector and with the same terms of employment, it seems unlikely that the large treatment effects found here are consistent with levels of churn of this kind. Especially since, as we show in Section 5.2, the results are particularly strong for longer-term jobs, for which churn is likely to be lower, and they are only detectable in the short run.

Third, the panel data help with us deal with concerns related to aggregation bias due to migration, since we observe reductions in wages for individuals who have not migrated.

5 Mechanisms

We now explore the mechanisms through which nominal wages adjust downwards after a typhoon hits. The results discussed so far are consistent with the adjustments one would predict from a spot market for labour where wages adjust to a market-clearing level, and unemployment does not increase but the total number of hours worked falls. Are these results driven by adjustment in wages for labour spot markets rather than long-term relationships? Indeed, if the results are concentrated among jobs governed by spot markets, the results could
be driven purely by a lower supply of labour hours, resulting in lower weekly and daily wage rates.

We start by showing that typhoon occurrence does not appear to affect measures of labour supply. 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 flexibility in implicit contracts. Finally, we explore heterogeneity in the estimated effects.

5.1 Market-clearing labour supply

We have argued that the results presented here are driven by reductions in labour demand, resulting in movements down the labour supply curve. Furthermore, downward wage flexibility seems to allow labour markets to clear: although the average hours per worker fall in response to storms, there is no impact on the rate of unemployment.

We 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 11 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 11 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). First, at the extensive margin, the lack of a rise in unemployment could be accounted for by movements along a very inelastic short-run labour supply curve. Wage flexibility in labour contracts allows for wages to fall, and for workers to keep their jobs. Workers are still happy to work at these reduced weekly wages, partly because they cannot afford to lose their entire wage incomes when storms hit. Secondly, workers may anticipate that the wage reduction will be short-lived (as our results on persistence suggest they usually are), and thus be willing to take lower salaries in the current quarter to ensure that they keep their jobs once wages rise again.

Second, at the intensive margin, we find some evidence that hourly wages adjust downwards, but that the main results are driven by reductions in the number of hours worked. This suggests movements along an individual labour supply curve that appears to be highly elastic. We cannot rule out that these results are also driven in part by shifts in the labour supply curve at the intensive margin. Storms do substantial damage to homes, farms and home enterprises, and workers might be willing to substitute labour away from wage-paying work to spend more time dealing with such problems at home. This substitution is mutually beneficial if firms simultaneously have less demand for worker hours when storms hit, which appears to be the case in the data.

5.2 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, rather than in the forms of labour for which wages are determined by spot 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 12. 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 4.7 per cent 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.

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 similar, but the adjustment margins differ greatly (Panel A of Table 12). 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 2.7 per cent reduction in their hourly wage.

The evidence suggests that the results are different between temporary and permanent jobs. Most striking is that 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 seems to suggest that even long-term permanent contract agreements exhibit high levels of flexibility. These findings are consistent with implicit contracts that allow state-contingent wages. 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 job.

Another mechanism by which labour markets adjust to storms deserves mention. While we are unable to detect any impact of storms on the probability of having a wage-paying job and on having worked positive hours at such a job, we establish that storms cause an increase in the probability that an individual reported working at wage-paying job, but not in the probability of receiving a wage (Panel B of Table 7). We find similar effects once we focus on the panel of individuals observed more than once (Table A.6). The effects on this outcome are small – they do not seem to be an important driver of the main results – but they suggest an interesting risk-sharing channel through which employers adjust to large shocks. Workers were not laid off, and did not stop working at their jobs, but they appear
not to receive their wages when storms hit, possibly because firms are unable to cover the costs of their salaries. Does this mean that employers compensated their workers later, after the major effects of the storms had passed? The results reported in Table A.3 indicate that wages are significantly less likely to be missing two quarters after storms hit. We interpret this as suggestive evidence that employers are more likely to pay workers in periods after the storms to make up for the weeks in which they were less likely to pay.

5.3 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.

5.3.1 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 affected 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.7). We find no significant heterogeneity between the rural and urban areas. All of the effect comes through the storm variable; the interaction term is not significant.\textsuperscript{22} One additional\textsuperscript{23}

\textsuperscript{22}This finding is robust to using municipal-level urbanization rates.
\textsuperscript{23}Although it is positive, suggesting that if anything, impacts are slightly bigger in rural areas.
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.7 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.

5.3.2 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 13). 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. 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.

[TABLE 13 HERE.]
6 Theoretical framework

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. 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.

24 Many models, including auction markets for daily labour, would show reductions in wages due to labour demand shocks. We need a model to explain why no lay-offs occur when firm labour demand is reduced.
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.

6.1 The model

In the model, the realized state of the world $\theta$ 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 $\theta$. Low realizations of $\theta$ 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 $\theta$. Therefore firms combine labour inputs through the function $f(.)$ with capital, prices and technology, all completely captured by $\theta$, 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 $\theta$ 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.\footnote{The results are not significantly altered by this assumption (see Miyazaki and Neary (1985) for a similar model with indemnity pay for laid-off workers), but it is likely to be true in our setting, and it makes the exposition considerably simpler. In many of the standard models unemployment is voluntary because laid off workers are indifferent between working and indemnity pay with additional leisure. Extensions of this}

Firm
profit is given:

\[ \pi = \theta f(pn, h) - wnp \]  

(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 \( \bar{w} \). 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:

\[ EU(\theta) = pU(w, h) + (1 - p)U(\bar{w}, 0) \]  

(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 \( \theta \). For ease of exposition, we write each endogenous variable without specifying it as a function of \( \theta \), \( (w, h, p) \). 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:

\[ Ev(\pi) = \bar{v} \]  

(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 \( (\lambda) \) and (2)

---

\( \text{framework add risk averse for firms (Blanchflower et al., 1996) or credit constrained firms such that profits are bounded at zero produce outcomes in which employment is involuntary. We largely ignore this question, and study a scenario in which employment is involuntary by construction.} \)

\( \text{This assumption is particularly likely to hold after large shocks, when new jobs are unlikely to be available in abundance.} \)

26
the total labour constraint \( p \leq 1 (\eta) \). 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:

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

\[
pU'_2(w, h) + \lambda v'(\pi)\theta f'_2(pn, h) = 0 \tag{7}
\]

\[
\eta = \lambda v'(\pi)[\theta n f'_1(pn, h) - wn] + U(w, h) - U(w, 0) \tag{8}
\]

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.

Equation 6 shows an important insight: when firms are risk neutral (\( v'(\pi) = 1 \)), wages respond to shocks to \( \theta \) 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.

---

\textsuperscript{27}Expected utility and profit are of course given by integrating the distribution of realizations for \( \theta \). \( Eu(\theta) = \int [p(\theta)U(w(\theta), h(\theta)) + (1 - \theta)U(\pi, 0)]dG(\theta) \). We do not specify the distribution of shocks \( G(\theta) \).

\textsuperscript{28}Worker risk aversion pushes in the other direction: workers bargain for wages to remain relatively constant (conditional on the hours worked remaining constant) in exchange for lower average wages.
6.1.1 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 \( \lambda \) from Equation 6:

\[
\begin{align*}
\theta f'_2(pn, h) &= -\frac{pU'_2(w, h)}{\lambda} \\
\theta f'_2(pn, h) &= -\frac{npU'_2(w, h)}{U'_1(w, h)}
\end{align*}
\]

Do firms adjust down the hours worked per worker \( h \) (work sharing) or reduce employment \( p \) (lay-offs) in response to bad realizations of \( \theta \)? This is determined by the value of \( \eta \) 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,\(^{29}\)

\(^{29}\)Wages are still state dependent in this case due to adjustments to the number of hours worked, as the point in the previous paragraph makes clear.
terms:
\[
\eta = \lambda n[\theta f'_1(pn, h) - \frac{h\theta f'_2(pn, h)}{pn} - \bar{w}]
+ U(w, h) - U(\bar{w}, 0) - (w - \bar{w})\lambda n + \frac{\lambda h\theta f'_2(pn, h)}{p} \tag{10}
\]

Then substituting from 9 and 6:
\[
\eta = \lambda n[\theta f'_1(pn, h) - \frac{h\theta f'_2(pn, h)}{pn} - \bar{w}]
+ U(w, h) - U(\bar{w}, 0) - (w - \bar{w})U'_1(w, h) - hU'_2(w, h) \tag{11}
\]
\[
\eta = \lambda n[\theta f'_1(pn, h) - \frac{h\theta f'_2(pn, h)}{pn} - \bar{w}] + H(w, h) \tag{12}
\]

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:
\[
n[\theta f'_1(n, h) - \bar{w}] < h\theta f'_2(n, h) \tag{13}
\]

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 \(\bar{w}\) 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 \((p = 1)\).
6.1.2 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 \( \eta \) becomes, at \( p = 1 \):

\[
\eta = -\lambda n\bar{w} + H(w, h) \\
= U(w, h) - U(\bar{w}, 0) - (w)U_1'(w, h) + hU_2'(w, h)
\]

(14)

Firms lay workers off depending on the opportunity cost of employment: the outside wage. Notice that if \( \bar{w} = 0 \), 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:

\[
f(np, h) = f(np\gamma(h))
\]

(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:

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

(16)

\(^{30}\)If workers are indifferent between employment and unemployment, such that \( U(w, h) = U(\bar{w}, 0) \), then lay-offs definitely do occur. This is similar to the result in Rosen (1985), in which firms provide full insurance to laid off workers, such that they are indifferent between employment and unemployment. In that model, by introducing indivisibility in labour (such that the returns on additional hours of work decrease for higher values of \( h \)) for sufficiently low \( \theta \), firms only lay off workers, and hours are constant.
Again with \( \bar{w} = 0 \), lay-offs happen only if:

\[
\gamma(h)/h < \gamma'(h)
\]  

(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 \( \theta \). Given the assumption of the ogive shape of \( \gamma \), 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 \( \gamma \) 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:

\[
\theta f'(.)\gamma'(h) = \frac{U_2'(w, h)}{U_1'(w, h)}
\]  

(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 \( w \), \( H(w, h) \) get very large, which makes lay-offs less likely, even when labour is relatively indivisible.

6.2 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.

7 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, as well as among workers in the form of work sharing. 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. Fourth, managers increase their working hours to respond to the shocks, which indicates that adequate management is an important component of a firm’s ability to deal with the shocks.
References


Figures

Figure 1: Storm damage by municipality (Sept-Dec 2006)
Figure 2: Percentage in wage changes for individuals who switch jobs and those that stay in the same jobs
### Table 1: Average municipality storm measures across all quarters (2003-2009)

<table>
<thead>
<tr>
<th>Measure</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max Windspeed</td>
<td>21064</td>
<td>13.146</td>
<td>29.819</td>
<td>142.96</td>
</tr>
<tr>
<td>Standardized Storm Measure</td>
<td>21064</td>
<td>.0320</td>
<td>.111</td>
<td>1</td>
</tr>
<tr>
<td>Any wind detected</td>
<td>21064</td>
<td>18.57%</td>
<td>38.88%</td>
<td></td>
</tr>
<tr>
<td>Storm Registered on SS-Scale</td>
<td>21064</td>
<td>10.60%</td>
<td>30.78%</td>
<td></td>
</tr>
<tr>
<td>SS class-0</td>
<td>21064</td>
<td>7.97%</td>
<td>27.08%</td>
<td></td>
</tr>
<tr>
<td>SS class-1</td>
<td>21064</td>
<td>4.60%</td>
<td>20.97%</td>
<td></td>
</tr>
<tr>
<td>SS class-2</td>
<td>21064</td>
<td>2.15%</td>
<td>14.50%</td>
<td></td>
</tr>
<tr>
<td>SS class-3</td>
<td>21064</td>
<td>2.02%</td>
<td>14.0%</td>
<td></td>
</tr>
<tr>
<td>SS class-4</td>
<td>21064</td>
<td>1.68%</td>
<td>12.87%</td>
<td></td>
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<tr>
<td>SS class-5</td>
<td>21064</td>
<td>.012%</td>
<td>3.57%</td>
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<tr>
<td>Big Storms (SS class-4&amp;5)</td>
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<td>1.81%</td>
<td>13.34%</td>
<td></td>
</tr>
<tr>
<td>Small Storms (SS class-1, 2&amp;3)</td>
<td>21064</td>
<td>8.7%</td>
<td>28.31%</td>
<td></td>
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</tbody>
</table>
Table 2: Descriptive statistics: Individual data

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<thead>
<tr>
<th>Variable</th>
<th>Full Sample</th>
<th></th>
<th>Panel</th>
<th></th>
</tr>
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<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Mean</td>
<td>Std. Dev.</td>
</tr>
<tr>
<td>Income per capita (PHP)</td>
<td>358.1</td>
<td>(768.9)</td>
<td>353.1</td>
<td>(762.0)</td>
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<tr>
<td>Average Wage (PHP)</td>
<td>1319</td>
<td>(954.1)</td>
<td>1318</td>
<td>(946.5)</td>
</tr>
<tr>
<td>Hours per worker</td>
<td>40.80</td>
<td>(19.4)</td>
<td>40.10</td>
<td>(19.2)</td>
</tr>
<tr>
<td>Employed</td>
<td>58.10%</td>
<td>(49.3)</td>
<td>61.1%</td>
<td>(48.7)</td>
</tr>
<tr>
<td>Unemployed</td>
<td>5.60%</td>
<td>(23.0)</td>
<td>5.10%</td>
<td>(21.9)</td>
</tr>
<tr>
<td>No schooling</td>
<td>2.30%</td>
<td>(14.8)</td>
<td>2.30%</td>
<td>(15.1)</td>
</tr>
<tr>
<td>Some primary</td>
<td>14.4%</td>
<td>(35.1)</td>
<td>15.4%</td>
<td>(36.1)</td>
</tr>
<tr>
<td>Primary graduate</td>
<td>14.9%</td>
<td>(35.6)</td>
<td>15.8%</td>
<td>(36.5)</td>
</tr>
<tr>
<td>Some secondary</td>
<td>17.3%</td>
<td>(37.8)</td>
<td>16.1%</td>
<td>(36.7)</td>
</tr>
<tr>
<td>Secondary graduate</td>
<td>24.2%</td>
<td>(42.8)</td>
<td>23.9%</td>
<td>(42.7)</td>
</tr>
<tr>
<td>Some college</td>
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<td>(44.4)</td>
<td>26.4%</td>
<td>(44.1)</td>
</tr>
<tr>
<td>Female</td>
<td>50%</td>
<td>(50)</td>
<td>50%</td>
<td>(50)</td>
</tr>
<tr>
<td>Age</td>
<td>35.80</td>
<td>(16.3)</td>
<td>37.40</td>
<td>(15.9)</td>
</tr>
<tr>
<td>Composition of jobs</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wage employment</td>
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<td>48.70%</td>
<td>(50.0)</td>
</tr>
<tr>
<td>Agriculture</td>
<td>35%</td>
<td>(47.7)</td>
<td>37.70%</td>
<td>(48.5)</td>
</tr>
<tr>
<td>Key Job Types</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Own farm</td>
<td>26.3%</td>
<td>(44.0)</td>
<td>28.7%</td>
<td>(45.3)</td>
</tr>
<tr>
<td>Wage farm</td>
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<td>(28.1)</td>
<td>8.90%</td>
<td>(28.5)</td>
</tr>
<tr>
<td>Self employed</td>
<td>22.2%</td>
<td>(41.6)</td>
<td>22.6%</td>
<td>(41.8)</td>
</tr>
<tr>
<td>Government</td>
<td>7.60%</td>
<td>(26.5)</td>
<td>8.10%</td>
<td>(27.2)</td>
</tr>
<tr>
<td>Private permanent</td>
<td>26.2%</td>
<td>(44.0)</td>
<td>23.6%</td>
<td>(42.4)</td>
</tr>
<tr>
<td>Private temporary</td>
<td>9.0%</td>
<td>(28.6)</td>
<td>8.10%</td>
<td>(27.3)</td>
</tr>
<tr>
<td>(N=3,402,456)</td>
<td></td>
<td></td>
<td>(N=1,000,687)</td>
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</table>
Table 3: Aggregate-level results

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

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 4: Decomposing the aggregate-level effects

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>inc/ adult</td>
<td>-0.078***</td>
<td>-0.035**</td>
<td>-0.020*</td>
<td>-0.015*</td>
<td>-0.032</td>
<td>-0.011</td>
</tr>
<tr>
<td>(0.024)</td>
<td>(0.014)</td>
<td>(0.010)</td>
<td>(0.009)</td>
<td>(0.023)</td>
<td>(0.007)</td>
<td></td>
</tr>
<tr>
<td>Small Storm</td>
<td>-0.012</td>
<td>-0.013**</td>
<td>-0.012**</td>
<td>-0.002</td>
<td>0.002</td>
<td>-0.001</td>
</tr>
<tr>
<td>(0.009)</td>
<td>(0.007)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.008)</td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>Denominator</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Adults</td>
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<td>20,808</td>
<td>20,808</td>
<td>20,808</td>
<td>20,808</td>
<td>20,808</td>
</tr>
<tr>
<td>Earners</td>
<td>0.073</td>
<td>0.131</td>
<td>0.146</td>
<td>0.068</td>
<td>0.024</td>
<td>0.016</td>
</tr>
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<td>Earned Hours</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hours</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Earners</td>
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<td></td>
<td></td>
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</table>

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: Aggregate-level results - Persistence

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

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 6: Individual-level results: Impacts on wages and employment

#### Panel A: Impact on Employment per Adult

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<tbody>
<tr>
<td>Big Storm</td>
<td>0.014*</td>
<td>-0.005</td>
<td>-0.005</td>
<td>-0.007*</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
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<tr>
<td>Small Storm</td>
<td>-0.012***</td>
<td>-0.001</td>
<td>-0.001</td>
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</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.002)</td>
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</tr>
<tr>
<td>R-squared</td>
<td>0.000</td>
<td>0.023</td>
<td>0.228</td>
<td>0.219</td>
</tr>
<tr>
<td>Mean Dep. Var</td>
<td>0.600</td>
<td>0.600</td>
<td>0.600</td>
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#### Panel B: Impact on Log of Weekly Wages

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<tr>
<td>Big Storm</td>
<td>-0.246***</td>
<td>-0.022*</td>
<td>-0.024**</td>
<td>-0.027**</td>
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<tr>
<td></td>
<td>(0.044)</td>
<td>(0.013)</td>
<td>(0.011)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Small Storm</td>
<td>0.105***</td>
<td>-0.005</td>
<td>-0.007</td>
<td>-0.010**</td>
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<tr>
<td></td>
<td>(0.019)</td>
<td>(0.006)</td>
<td>(0.005)</td>
<td>(0.005)</td>
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<tr>
<td>Observations</td>
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<td>860,809</td>
<td>860,809</td>
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<td>R-squared</td>
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<td>0.216</td>
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<td>Mean Dep. Var</td>
<td>6.900</td>
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<td>6.900</td>
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</tbody>
</table>

**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 7: Individual-level results: decomposition

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<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Impact on Intensive Margins (Earnings and Hours)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>wage/week</td>
<td>hours/worker</td>
<td>hours/earner</td>
<td>wage/hour</td>
<td>days/earner</td>
<td>hours/day</td>
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<tr>
<td>Big Storm</td>
<td>-0.027**</td>
<td>-0.018**</td>
<td>-0.016*</td>
<td>-0.011</td>
<td>-0.015**</td>
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<td>(0.008)</td>
<td>(0.007)</td>
<td>(0.004)</td>
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<tr>
<td>Small Storm</td>
<td>-0.010**</td>
<td>-0.008**</td>
<td>-0.003</td>
<td>-0.007*</td>
<td>-0.001</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Sample</td>
<td>Earners</td>
<td>All</td>
<td>Earners</td>
<td>Earners</td>
<td>Earners</td>
<td>Earners</td>
</tr>
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<td>Observations</td>
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<td>0.128</td>
<td>0.094</td>
<td>0.417</td>
<td>0.093</td>
<td>0.039</td>
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<tr>
<td><strong>Panel B: Impact on Extensive Margins</strong></td>
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</tr>
<tr>
<td></td>
<td>employed</td>
<td>job</td>
<td>wage missing</td>
<td>wage observed</td>
<td>zero hours</td>
<td>lost job quarter</td>
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<td>Big Storm</td>
<td>-0.007*</td>
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<td>0.006</td>
<td>-0.006*</td>
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<tr>
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<td>(0.004)</td>
<td>(0.006)</td>
<td>(0.004)</td>
<td>(0.001)</td>
<td>(0.002)</td>
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<tr>
<td>Small Storm</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.001</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.002**</td>
</tr>
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</tr>
<tr>
<td>Sample</td>
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<td>All</td>
<td>Earners</td>
<td>All</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>R-squared</td>
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<td>Mean Dep. Var</td>
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<td>0.581</td>
<td>0.507</td>
<td>0.286</td>
<td>0.009</td>
<td>0.030</td>
</tr>
</tbody>
</table>

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 8: Individual-level results: Employment in different types of jobs

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<td>Self-Employed</td>
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<td>Private Sector Temporary</td>
<td>Farming Own</td>
<td>Farming Wage</td>
<td>Government</td>
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<td><strong>Panel A: Total Effect (Unconditional on having a job)</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Big Storm</td>
<td>-0.005**</td>
<td>-0.001</td>
<td>-0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Small Storm</td>
<td>0.000</td>
<td>-0.002</td>
<td>0.001</td>
<td>0.001</td>
<td>0.000</td>
<td>0.000</td>
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<tr>
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</tr>
<tr>
<td>R-squared</td>
<td>0.056</td>
<td>0.092</td>
<td>0.028</td>
<td>0.247</td>
<td>0.115</td>
<td>0.073</td>
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<tr>
<td>Mean Dep. Var</td>
<td>0.131</td>
<td>0.169</td>
<td>0.057</td>
<td>0.127</td>
<td>0.046</td>
<td>0.043</td>
</tr>
<tr>
<td><strong>Panel B: Composition Effect (Conditional on having a job)</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Big Storm</td>
<td>-0.006</td>
<td>0.002</td>
<td>-0.001</td>
<td>0.004</td>
<td>0.000</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Small Storm</td>
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<td>-0.002</td>
<td>0.002</td>
<td>0.001</td>
<td>0.000</td>
<td>0.000</td>
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<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
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</tr>
<tr>
<td>Observations</td>
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<td>1,453,619</td>
<td>1,453,619</td>
<td>1,453,619</td>
<td>1,453,619</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.084</td>
<td>0.170</td>
<td>0.065</td>
<td>0.315</td>
<td>0.160</td>
<td>0.113</td>
</tr>
<tr>
<td>Mean Dep. Var</td>
<td>0.226</td>
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<td>0.217</td>
<td>0.078</td>
<td>0.079</td>
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<tr>
<td><strong>Panel C: Composition Effect (Conditional on earning a wage)</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Big Storm</td>
<td>0.001</td>
<td>-0.000</td>
<td>0.005</td>
<td>-0.001</td>
<td>0.004</td>
<td>-0.009**</td>
</tr>
<tr>
<td></td>
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<td>(0.009)</td>
<td>(0.007)</td>
<td>(0.001)</td>
<td>(0.006)</td>
<td>(0.004)</td>
</tr>
<tr>
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<td>-0.001</td>
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<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.000)</td>
<td>(0.003)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Observations</td>
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<td>669,711</td>
<td>669,711</td>
<td>669,711</td>
<td>669,711</td>
<td>669,711</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.005</td>
<td>0.145</td>
<td>0.073</td>
<td>0.023</td>
<td>0.366</td>
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<tr>
<td>Mean Dep. Var</td>
<td>0.005</td>
<td>.54</td>
<td>.183</td>
<td>.001</td>
<td>.132</td>
<td>.127</td>
</tr>
</tbody>
</table>

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 9: Individual results: Impacts on composition of the sample

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<td>Panel A: Impact on the Characteristic (Composition) of the Full Sample</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>-0.001</td>
<td>-0.001</td>
<td>0.003</td>
<td>0.004</td>
<td>-0.003</td>
<td>-0.003</td>
</tr>
<tr>
<td>Small Storm</td>
<td>0.001</td>
<td>0.084*</td>
<td>0.001</td>
<td>0.000</td>
<td>0.001</td>
<td>-0.003**</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.002</td>
<td>0.010</td>
<td>0.023</td>
<td>0.080</td>
<td>0.038</td>
<td>0.008</td>
<td>0.032</td>
<td>0.072</td>
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<td>Mean Dep. Var</td>
<td>0.510</td>
<td>36.070</td>
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<td>0.130</td>
<td>0.150</td>
<td>0.160</td>
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Panel B: Impact on the Characteristic (Composition) of the Individuals Employed

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<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big Storm</td>
<td>0.002</td>
<td>0.150</td>
<td>-0.000</td>
<td>-0.002</td>
<td>0.006</td>
<td>0.005</td>
<td>-0.009**</td>
<td>-0.001</td>
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<td>Small Storm</td>
<td>0.004**</td>
<td>0.031</td>
<td>0.000</td>
<td>-0.000</td>
<td>0.001</td>
<td>-0.003**</td>
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</tr>
<tr>
<td>Observations</td>
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<td>1,453,619</td>
<td>1,453,619</td>
<td>1,453,619</td>
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<td>1,453,619</td>
</tr>
<tr>
<td>R-squared</td>
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<td>0.016</td>
<td>0.041</td>
<td>0.106</td>
<td>0.048</td>
<td>0.010</td>
<td>0.043</td>
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<tr>
<td>Mean Dep. Var</td>
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<td>0.17</td>
<td>0.13</td>
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<td>0.28</td>
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</table>

Panel C: Impact on the Characteristic (Composition) of the Individuals Earning a Wage

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<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
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</thead>
<tbody>
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<td>Big Storm</td>
<td>0.009</td>
<td>0.431**</td>
<td>0.000</td>
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<td>0.007</td>
<td>0.008</td>
<td>-0.013**</td>
<td>0.000</td>
</tr>
<tr>
<td>Small Storm</td>
<td>0.006**</td>
<td>0.091</td>
<td>-0.000</td>
<td>-0.001</td>
<td>-0.000</td>
<td>-0.003</td>
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<td>0.002</td>
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<tr>
<td>Observations</td>
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<td>669,711</td>
<td>669,711</td>
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<td>669,711</td>
<td>669,711</td>
<td>669,711</td>
<td>669,711</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.017</td>
<td>0.015</td>
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<td>0.012</td>
<td>0.035</td>
<td>0.075</td>
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<td>36.07</td>
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<td>0.15</td>
<td>0.16</td>
<td>0.26</td>
<td>0.28</td>
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</tbody>
</table>

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 10: Panel-level results: decomposition

#### Panel A: Impact on Earnings and Hours (All Employees)

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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>wage/ week</td>
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<td>hours/ earner</td>
<td>wage/ hour</td>
<td>days/ earner</td>
<td>hours/ day</td>
</tr>
<tr>
<td>Big Storm</td>
<td>-0.034***</td>
<td>-0.025**</td>
<td>-0.024**</td>
<td>-0.017*</td>
<td>-0.014*</td>
<td>-0.011**</td>
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<tr>
<td></td>
<td>(0.012)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.009)</td>
<td>(0.008)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Small Storm</td>
<td>-0.010</td>
<td>-0.011**</td>
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<td>277,932</td>
<td>267,038</td>
<td>277,928</td>
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<tr>
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<td>0.131</td>
<td>0.107</td>
<td>0.439</td>
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#### Panel B: Impact on Earnings and Hours (Same Job Type)

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<td>hours/ earner</td>
<td>wage/ hour</td>
<td>days/ earner</td>
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<tr>
<td>Big Storm</td>
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<td>-0.020*</td>
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<td>-0.018*</td>
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<td>(0.011)</td>
<td>(0.009)</td>
<td>(0.005)</td>
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<tr>
<td>Small Storm</td>
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<td>-0.007</td>
<td>0.007</td>
<td>-0.010*</td>
<td>0.002</td>
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<td>195,726</td>
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<td>R-squared</td>
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<td>0.146</td>
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<td>0.462</td>
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<td>Mun Fe</td>
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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 11: Individual-level and panel-level results: Labour supply

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</tr>
<tr>
<td>in labour force</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>searched for work</td>
<td>-0.005</td>
<td>0.002</td>
<td>0.004</td>
<td>-0.002</td>
<td>0.002</td>
<td>0.001</td>
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<tr>
<td>no work</td>
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<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.003)</td>
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<td>(0.006)</td>
</tr>
<tr>
<td>Big Storm</td>
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<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small Storm</td>
<td>0.002</td>
<td>-0.004**</td>
<td>0.003*</td>
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<tr>
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<td>2,464,172</td>
<td>1,588,750</td>
<td>1,010,552</td>
<td>1,430,353</td>
<td>1,098,598</td>
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<tr>
<td>R-squared</td>
<td>0.233</td>
<td>0.043</td>
<td>0.060</td>
<td>0.063</td>
<td>0.114</td>
<td>0.104</td>
</tr>
<tr>
<td>Mean Dep. Var</td>
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<td>0.066</td>
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<td>0.093</td>
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<tr>
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</tr>
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<td>-0.003</td>
<td>-0.001</td>
<td>-0.005</td>
<td>-0.003</td>
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<td>0.005</td>
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<tr>
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<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.010)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Big Storm</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>-0.004*</td>
<td>0.001</td>
<td>-0.002</td>
<td>0.007</td>
<td>0.007**</td>
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<td>(0.002)</td>
<td>(0.002)</td>
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<td>(0.004)</td>
</tr>
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<td>1,294,842</td>
<td>1,294,842</td>
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<td>699,704</td>
<td>455,862</td>
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<td>R-squared</td>
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<td>0.002</td>
<td>0.002</td>
<td>0.001</td>
<td>0.005</td>
<td>0.016</td>
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<tr>
<td>Mean Dep. Var</td>
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<td>0.070</td>
<td>0.603</td>
<td>0.047</td>
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</table>

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

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<tr>
<td></td>
<td>wage/ week</td>
<td>hours/ worker</td>
<td>hours/ earner</td>
<td>wage/ hour</td>
<td>days/ earner</td>
<td>hours/ day</td>
</tr>
<tr>
<td>Big Storm</td>
<td>0.002</td>
<td>-0.031***</td>
<td>-0.021</td>
<td>0.020</td>
<td>-0.031**</td>
<td>0.010*</td>
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<td>(0.011)</td>
<td>(0.014)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.006)</td>
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<tr>
<td>Small Storm</td>
<td>-0.017*</td>
<td>-0.003</td>
<td>-0.003</td>
<td>-0.013*</td>
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<td>-0.001</td>
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<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.008)</td>
<td>(0.005)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Big Storm * priv</td>
<td>-0.049**</td>
<td>0.055***</td>
<td>0.010</td>
<td>-0.056***</td>
<td>0.028**</td>
<td>-0.019***</td>
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<td>(0.016)</td>
<td>(0.019)</td>
<td>(0.014)</td>
<td>(0.007)</td>
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<tr>
<td>Small Storm * priv</td>
<td>0.014</td>
<td>-0.017*</td>
<td>-0.001</td>
<td>0.013</td>
<td>0.001</td>
<td>-0.002</td>
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<tr>
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<th>Earners</th>
<th>Earners</th>
<th>Earners</th>
<th>Earners</th>
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<td>669,711</td>
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<td>R-squared</td>
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<td>0.156</td>
<td>0.124</td>
<td>0.441</td>
<td>0.119</td>
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Panel A: Decomposition of Impacts among Private Sector Wage Employment and Other Jobs

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<td></td>
<td>wage/ week</td>
<td>hours/ worker</td>
<td>hours/ earner</td>
<td>wage/ hour</td>
<td>days/ earner</td>
<td>hours/ day</td>
</tr>
<tr>
<td>Big Storm * permanent</td>
<td>-0.024**</td>
<td>0.003</td>
<td>0.003</td>
<td>-0.027**</td>
<td>0.003</td>
<td>-0.001</td>
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<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.012)</td>
<td>(0.007)</td>
<td>(0.005)</td>
</tr>
<tr>
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<td>-0.009</td>
<td>0.000</td>
<td>0.003</td>
<td>-0.012**</td>
<td>0.002</td>
<td>0.001</td>
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<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.006)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Big Storm * temporary</td>
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<td>-0.064***</td>
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<td>-0.044***</td>
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<td>(0.014)</td>
<td>(0.010)</td>
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<td>0.014</td>
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<td>-0.007</td>
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<td>(0.010)</td>
<td>(0.010)</td>
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<td>465,245</td>
<td>465,245</td>
<td>465,245</td>
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<td>0.395</td>
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<td>1.221</td>
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<td>0.008</td>
<td>0.021</td>
<td>0.003</td>
<td>0.269</td>
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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 13: Individuals-level results: Heterogenous treatment effects by managerial and non-managerial private sector jobs

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<td></td>
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<td>wage/</td>
<td>days/</td>
<td>hours/</td>
</tr>
<tr>
<td></td>
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<td>worker</td>
<td>earner</td>
<td>hour</td>
<td>earner</td>
<td>day</td>
</tr>
<tr>
<td>Big Storm * non manag</td>
<td>-0.035***</td>
<td>-0.035***</td>
<td>-0.021**</td>
<td>-0.017*</td>
<td>-0.019**</td>
<td>-0.003</td>
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<tr>
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<td>(0.010)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.005)</td>
</tr>
<tr>
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<td>-0.011**</td>
<td>-0.005</td>
<td>-0.006</td>
<td>-0.002</td>
<td>-0.003</td>
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<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Big Storm * manag</td>
<td>0.199**</td>
<td>0.141***</td>
<td>0.176***</td>
<td>0.008</td>
<td>0.092***</td>
<td>0.081***</td>
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<td>(0.021)</td>
<td>(0.024)</td>
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<td>(0.012)</td>
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Sample

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<th>Earners</th>
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<td>566,279</td>
<td>575,322</td>
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<td>0.000</td>
<td>0.795</td>
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</tr>
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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.
Online Appendix: Background on the Labor Force Survey

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

A.1 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.

A.2 Questionnaire

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

A.2.1 Employment

For each household member above the age 15, the enumerators ask the following question: *Did (NAME) do any work for at least 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.

A.2.2 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.
A.2.3 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.

A.3 Sampling

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

A.3.1 Sampling Procedure

The 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.

A.3.2 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.
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. ERIGTA
Administrator
National Statistics Office
P.O Box 779, Manila

---

**Identification and Other Information**

<table>
<thead>
<tr>
<th>Geographic Identification Codes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Province ______________________</td>
</tr>
<tr>
<td>Mun/City ______________________</td>
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<tr>
<td>Bgy __________________________</td>
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<td>EA ____________________________</td>
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<td>SHSN __________________________</td>
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<th>Design Code</th>
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<tr>
<td>Replicate __________________________</td>
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<tr>
<td>Stratum __________________________</td>
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<tr>
<td>PSU No. __________________________</td>
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<tr>
<td>Rotation Group ____________________</td>
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<tr>
<td>Number of Households in the housing unit __________</td>
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</table>

<table>
<thead>
<tr>
<th>Name of Respondent:</th>
<th>Line No.</th>
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<tbody>
<tr>
<td>____________________</td>
<td>_______</td>
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<table>
<thead>
<tr>
<th>Name of Household Head:</th>
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<tbody>
<tr>
<td>______________________</td>
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</table>

<table>
<thead>
<tr>
<th>Address:</th>
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<td>_________</td>
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<table>
<thead>
<tr>
<th>Interview Status (Encircle appropriate code and enter in the box provided)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Completed Interview</td>
</tr>
<tr>
<td>2 Refusal</td>
</tr>
<tr>
<td>3 Temporarily away/ Not at home/ On vacation</td>
</tr>
<tr>
<td>4 Vacant housing Unit</td>
</tr>
<tr>
<td>5 Housing unit demolished, destroyed by fire, typhoon, etc.</td>
</tr>
<tr>
<td>6 Others, specify ______________</td>
</tr>
<tr>
<td>7 Critical area, flooded area</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Household Auxiliary Information (Encircle appropriate code and enter in the box provided)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Household same as in previous quarter, go to question A</td>
</tr>
<tr>
<td>2 New occupant of old sampled housing unit, proceed with interview</td>
</tr>
<tr>
<td>3 Rotated household, proceed with interview</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Certification</th>
</tr>
</thead>
<tbody>
<tr>
<td>I hereby certify that the data gathered in this questionnaire were obtained/reviewed by me personally and in accordance with instructions.</td>
</tr>
</tbody>
</table>

Signature over Printed Name of Enumerator Date Accomplished

Signature over Printed Name of Supervisor Date Reviewed

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
<table>
<thead>
<tr>
<th>Line No.</th>
<th>En-circle respondent</th>
<th>Household member as of date of visit (Last name, first name)</th>
<th>Is new member of this house hold? 1 Y 2 N</th>
<th>What was line number in the previous quarter?</th>
<th>Relationship to HH head S 1 M 2 F</th>
<th>Age as of last birthday (Check col.7A for members 5 years old and over)</th>
<th>Sex</th>
<th>Marital civil status (Enter code)</th>
<th>Highest grade completed (Enter code/specify degree)</th>
<th>Is currently attending school? 1 Y 2 N</th>
<th>Overseas Filipino Indicator (Enter Code)</th>
<th>Did you do any work for at least one hour during the past week? 1 YES 2 NO</th>
<th>Although you did not work, did you have a job or business during the past week? 1 YES 2 NO, skip to Col. 14</th>
<th>1 YES, skip to Col. 14 2 NO</th>
<th>Don not fill</th>
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**Codes for Col. 5 - Relationship**
- 01 - Head
- 02 - Wife/Husband
- 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**
- 01 - Single
- 02 - Married
- 03 - Widowed
- 04 - Divorced/Separated
- 05 - Unknown

**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

**Codes for Col.11 - Overseas Filipino Indicator**
- 01 - OCW
- 02 - Workers other than OCW
- 03 - Employees in Phil. Embassy, Consulates & other missions
- 04 - Students abroad/tourists
- 05 - Others

**For College Graduate**
Specify the bachelor's or higher degree completed and field of study.
<table>
<thead>
<tr>
<th>Line No.</th>
<th>Col. No.</th>
<th>Others, Specify</th>
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</thead>
<tbody>
<tr>
<td></td>
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</table>

### Computation for Basic Pay

#### Codes for Col. 18 - Nature of Employment
- **1**: Permanent job/business/industry
  - 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/private 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 wages/salary)
  - **1**: Per piece
  - **2**: Per hour
  - **3**: Per day
  - **4**: Monthly
  - **5**: Pakyaw
  - **6**: Other salaries/wages (Specify)
  - **7**: Net salaries/wages (Specify, e.g. commission basis)

#### Codes for Col. 26 - Basis of Payment
- **0**: In kind, imputed (received as wages/salary)
- **1**: Per piece
- **2**: Per hour
- **3**: Per day
- **4**: Monthly
- **5**: Pakyaw
- **6**: Other salaries/wages (Specify)
- **7**: Net 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)
**ECONOMIC CHARACTERISTICS (15 YEARS OLD AND OVER)**

2. For persons who did not work and had no job/business during the past week

| Line No. | Col. No. | Others, Specify | Remarks |

### Activity during the past quarter

<table>
<thead>
<tr>
<th>Did ____ work at all or had a job or business during the past quarter?</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 YES</td>
</tr>
<tr>
<td>2 NO</td>
</tr>
</tbody>
</table>

### Kind of business/industry

<p>| |</p>
<table>
<thead>
<tr>
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<tbody>
<tr>
<td>(Specify industry e.g. public school, palay farm, etc.)</td>
</tr>
</tbody>
</table>

### Job Search Method

<table>
<thead>
<tr>
<th>Codes for Col. 33</th>
</tr>
</thead>
<tbody>
<tr>
<td>Job Search Method</td>
</tr>
<tr>
<td>1 - Registered in public employment agency</td>
</tr>
<tr>
<td>2 - Registered in private employment agency</td>
</tr>
<tr>
<td>3 - Approached employer directly</td>
</tr>
<tr>
<td>4 - Approached relatives or friends</td>
</tr>
<tr>
<td>5 - Placed or answered advertisements</td>
</tr>
<tr>
<td>6 - Other, specify</td>
</tr>
</tbody>
</table>

### Reasons not looking for work

<table>
<thead>
<tr>
<th>Codes for Col. 36</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reasons not looking for work</td>
</tr>
<tr>
<td>1 - Tired/believe no work available</td>
</tr>
<tr>
<td>2 - Awaiting results of previous job application</td>
</tr>
<tr>
<td>3 - Temporary illness/disability</td>
</tr>
<tr>
<td>4 - Bad weather</td>
</tr>
<tr>
<td>5 - Waiting for rehire/job recall</td>
</tr>
<tr>
<td>6 - Too young/old or retired/permanent disability</td>
</tr>
<tr>
<td>7 - Household, family duties</td>
</tr>
<tr>
<td>8 - Schooling</td>
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<tr>
<td>9 - Others, specify</td>
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</tbody>
</table>

### Last time to look for work

<table>
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<tr>
<th>Codes for Col. 36</th>
</tr>
</thead>
<tbody>
<tr>
<td>Last time to look for work</td>
</tr>
<tr>
<td>1 - Within last month</td>
</tr>
<tr>
<td>2 - One to six months ago</td>
</tr>
<tr>
<td>3 - More than six months ago</td>
</tr>
</tbody>
</table>

---

**Legend:**

- Col. 33: Job Search Method
- Col. 34: Reasons not looking for work
- Col. 35: Last time to look for work
- Col. 36: Go to next hh member
- Col. 37: Skip to Col. 38
- Col. 38: Go to next hh member
## Online Appendix: Additional Results

### Table A.1: Aggregate-level results (income per capita): Alternative storm measures

<table>
<thead>
<tr>
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<th>(1)</th>
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<th>(3)</th>
<th>(4)</th>
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</thead>
<tbody>
<tr>
<td>Wind-speed (knots)</td>
<td>-0.00027**</td>
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</tr>
<tr>
<td></td>
<td>(0.000)</td>
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<tr>
<td>Normalized Wind-speed (0-1)</td>
<td>-0.076***</td>
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<td></td>
<td>(0.025)</td>
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<td>(0.012)</td>
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<td>ss scale 2</td>
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<td>ss scale 4</td>
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<td></td>
<td>(0.023)</td>
<td></td>
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</tr>
<tr>
<td>ss scale 5</td>
<td>-0.118</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.072)</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Big Storm</td>
<td></td>
<td></td>
<td>-0.078***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.024)</td>
<td></td>
</tr>
<tr>
<td>Small Storm</td>
<td></td>
<td></td>
<td>-0.012</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.009)</td>
<td></td>
</tr>
</tbody>
</table>

| 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, 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.2: Aggregate-level results (employment): Alternative storm measures

<table>
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<tr>
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<th>(4) employed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind-speed (knots)</td>
<td>0.000</td>
<td>(0.000)</td>
<td></td>
<td></td>
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<tr>
<td>Normalized Wind-speed (0-1)</td>
<td></td>
<td>-0.005</td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>ss scale 1</td>
<td>0.001</td>
<td>(0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ss scale 2</td>
<td>0.006</td>
<td>(0.005)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ss scale 3</td>
<td>-0.007*</td>
<td>(0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ss scale 4</td>
<td>-0.007*</td>
<td>(0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ss scale 5</td>
<td>-0.007</td>
<td>(0.007)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Big Storm</td>
<td>-0.007*</td>
<td>(0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small Storm</td>
<td>0.000</td>
<td>(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>21,064</td>
<td>21,064</td>
<td>21,064</td>
<td>21,064</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.021</td>
<td>0.021</td>
<td>0.021</td>
<td>0.021</td>
</tr>
<tr>
<td>Mean Dep. Var</td>
<td>0.600</td>
<td>0.600</td>
<td>0.600</td>
<td>0.600</td>
</tr>
</tbody>
</table>

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.3: Individual-level results: persistence

<table>
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</thead>
<tbody>
<tr>
<td></td>
<td>Current</td>
<td>Lag 1</td>
<td>Lag 2</td>
<td>Lag 3</td>
<td>Current</td>
<td>Lag 1</td>
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<tr>
<td><strong>Big Storm</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Current</td>
<td>-0.022**</td>
<td>-0.012</td>
<td>0.004</td>
<td>-0.018</td>
<td>-0.005</td>
<td>-0.005</td>
</tr>
<tr>
<td>(0.011)</td>
<td>(0.014)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.005)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Lag 1</td>
<td>0.005</td>
<td>0.005</td>
<td>0.016*</td>
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<td>-0.003</td>
<td>-0.002</td>
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<tr>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.011)</td>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.004)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Lag 2</td>
<td>-0.012</td>
<td>0.026***</td>
<td>-0.012</td>
<td>0.008</td>
<td>0.007*</td>
<td>-0.002</td>
</tr>
<tr>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.009)</td>
<td>(0.005)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Lag 3</td>
<td>-0.005</td>
<td>0.005</td>
<td>-0.010</td>
<td>-0.008</td>
<td>-0.007</td>
<td>-0.003</td>
</tr>
<tr>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.009)</td>
<td>(0.008)</td>
<td>(0.005)</td>
<td>(0.002)</td>
</tr>
<tr>
<td><strong>Small Storm</strong></td>
<td>(lags estimated but not displayed)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Current</td>
<td>-0.005</td>
<td>-0.002</td>
<td>0.002</td>
<td>-0.002</td>
<td>-0.002</td>
<td>0.000</td>
</tr>
<tr>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Sample</td>
<td>Earners</td>
<td>All</td>
<td>Earners</td>
<td>Earners</td>
<td>Earners</td>
<td>Earners</td>
</tr>
<tr>
<td>Observations</td>
<td>860,809</td>
<td>2,006,022</td>
<td>860,809</td>
<td>860,809</td>
<td>860,809</td>
<td>860,809</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.444</td>
<td>0.130</td>
<td>0.092</td>
<td>0.419</td>
<td>0.090</td>
<td>0.040</td>
</tr>
</tbody>
</table>

|               | (1)          | (2)          | (3)          | (4)          | (5)          | (6)          |
|               | Employed     | Job          | Wage         | Wage         | Zero          | Lost job     |
| **Big Storm** |              |              | Missing      | Observed     | Hours         | Quarter      |
| Current       | -0.006       | -0.005       | 0.006        | -0.006*      | 0.001        | 0.001        |
| (0.004)       | (0.004)      | (0.006)      | (0.006)      | (0.004)      | (0.001)      | (0.002)      |
| Lag 1         | -0.003       | -0.006*      | 0.004        | -0.003       | -0.003***    | -0.002       |
| (0.004)       | (0.004)      | (0.006)      | (0.006)      | (0.004)      | (0.001)      | (0.002)      |
| Lag 2         | 0.000        | -0.004       | -0.014**     | 0.006*       | -0.004***    | -0.001       |
| (0.004)       | (0.004)      | (0.006)      | (0.004)      | (0.001)      | (0.002)      | (0.002)      |
| Lag 3         | -0.004       | -0.005       | 0.006        | -0.006       | -0.001       | 0.000        |
| (0.004)       | (0.004)      | (0.006)      | (0.004)      | (0.001)      | (0.002)      | (0.002)      |
| **Small Storm** | (lags estimated but not displayed) |              |              |              |              |              |
| Current       | -0.001       | -0.001       | 0.001        | -0.001       | 0.000        | -0.002**     |
| (0.002)       | (0.002)      | (0.002)      | (0.002)      | (0.000)      | (0.001)      | (0.001)      |
| Sample        | All          | All          | Earners      | All          | All          | All          |
| 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.4: Panel-level results: Employment in different types of jobs

<table>
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<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Self-</td>
<td>Private</td>
<td>Farming</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Employed</td>
<td>Sector</td>
<td>Own</td>
<td>Wage</td>
<td>Government</td>
<td></td>
</tr>
<tr>
<td>Big Storm</td>
<td>-0.003</td>
<td>-0.002</td>
<td>-0.000</td>
<td>0.001</td>
<td>0.001</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Small Storm</td>
<td>-0.000</td>
<td>-0.002</td>
<td>0.001</td>
<td>0.000</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Observations</td>
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<td>1,294,842</td>
<td>1,294,842</td>
<td>1,294,842</td>
<td>1,294,842</td>
<td>1,294,842</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.017</td>
<td>0.059</td>
<td>0.017</td>
<td>0.196</td>
<td>0.082</td>
<td>0.015</td>
</tr>
<tr>
<td>Mean Dep. Var</td>
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<td>0.161</td>
<td>0.054</td>
<td>0.148</td>
<td>0.051</td>
<td>0.048</td>
</tr>
</tbody>
</table>

### Panel A: Total Effect (Unconditional on having a job)

<table>
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<tr>
<th></th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Self-</td>
<td>Private</td>
<td>Farming</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Employed</td>
<td>Sector</td>
<td>Own</td>
<td>Wage</td>
<td>Government</td>
<td></td>
</tr>
<tr>
<td>Big Storm</td>
<td>-0.003</td>
<td>-0.004</td>
<td>-0.000</td>
<td>0.005</td>
<td>0.002</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.006)</td>
<td>(0.005)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Small Storm</td>
<td>-0.000</td>
<td>-0.003</td>
<td>0.002</td>
<td>0.002</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Observations</td>
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<td>805,430</td>
<td>805,430</td>
<td>805,430</td>
<td>805,430</td>
<td>805,430</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.040</td>
<td>0.144</td>
<td>0.036</td>
<td>0.263</td>
<td>0.118</td>
<td>0.026</td>
</tr>
<tr>
<td>Mean Dep. Var</td>
<td>0.230</td>
<td>0.263</td>
<td>0.089</td>
<td>0.241</td>
<td>0.084</td>
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### Panel A: Composition Effect (Conditional on having a job)

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<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<tbody>
<tr>
<td></td>
<td>Self-</td>
<td>Private</td>
<td>Farming</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Employed</td>
<td>Sector</td>
<td>Own</td>
<td>Wage</td>
<td>Government</td>
<td></td>
</tr>
<tr>
<td>Big Storm</td>
<td>0.001</td>
<td>-0.003</td>
<td>0.004</td>
<td>-0.001</td>
<td>0.007</td>
<td>-0.007</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.009)</td>
<td>(0.007)</td>
<td>(0.001)</td>
<td>(0.007)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Small Storm</td>
<td>-0.000</td>
<td>-0.006</td>
<td>0.008**</td>
<td>0.001</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.001)</td>
<td>(0.004)</td>
<td>(0.003)</td>
</tr>
<tr>
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<td>396,552</td>
<td>396,552</td>
<td>396,552</td>
<td>396,552</td>
<td>396,552</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.005</td>
<td>0.148</td>
<td>0.039</td>
<td>0.044</td>
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<td>Mean Dep. Var</td>
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<td>0.502</td>
<td>0.170</td>
<td>0.002</td>
<td>0.160</td>
<td>0.149</td>
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</table>

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.5: Panel results: Comparison of municipal and individual fixed effects (Decomposition)

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<th>Panel A: All Employees</th>
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<td>panel wage/ week</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Big Storm</td>
<td>-0.019**</td>
<td>-0.022**</td>
<td>-0.031**</td>
<td>-0.034***</td>
</tr>
<tr>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.012)</td>
<td>(0.012)</td>
<td></td>
</tr>
<tr>
<td>Small Storm</td>
<td>-0.008</td>
<td>-0.009*</td>
<td>-0.006</td>
<td>-0.010</td>
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<tr>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>349,605</td>
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<td>349,605</td>
<td>267,038</td>
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<tr>
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<td>0.022</td>
<td>0.460</td>
<td>0.465</td>
</tr>
<tr>
<td>FE</td>
<td>Ind</td>
<td>Ind</td>
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<td>Muni</td>
</tr>
<tr>
<td>Mindanao</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: All Employees with similar jobs</th>
<th>(1)</th>
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<th>(3)</th>
<th>(4)</th>
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</thead>
<tbody>
<tr>
<td>panel wage/ week</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Big Storm</td>
<td>-0.023**</td>
<td>-0.027**</td>
<td>-0.026</td>
<td>-0.031*</td>
</tr>
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<td>(0.011)</td>
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<td>(0.017)</td>
<td>(0.017)</td>
<td></td>
</tr>
<tr>
<td>Small Storm</td>
<td>-0.007</td>
<td>-0.011*</td>
<td>0.002</td>
<td>-0.002</td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.008)</td>
<td>(0.008)</td>
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</tr>
<tr>
<td>Observations</td>
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<td>125,078</td>
<td>163,043</td>
<td>125,078</td>
</tr>
<tr>
<td>R-squared</td>
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<td>0.021</td>
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<td>0.523</td>
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<tr>
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<td>Ind</td>
<td>Ind</td>
<td>Muni</td>
<td>Muni</td>
</tr>
<tr>
<td>Mindanao</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

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.6: Panel-level results: Employment

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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big Storm</td>
<td>employed</td>
<td>job</td>
<td>wage</td>
<td>wage</td>
<td>zero</td>
<td>lost job</td>
</tr>
<tr>
<td></td>
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<td></td>
<td>missing</td>
<td>observed</td>
<td>hours</td>
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</tr>
<tr>
<td></td>
<td>-0.005</td>
<td>-0.004</td>
<td>0.009*</td>
<td>-0.007**</td>
<td>0.003</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Small Storm</td>
<td>0.001</td>
<td>0.001</td>
<td>0.003</td>
<td>0.000</td>
<td>0.001</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
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<td>(0.002)</td>
</tr>
</tbody>
</table>

<table>
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<tr>
<th></th>
<th>Observations</th>
<th>1,294,842</th>
<th>1,294,842</th>
<th>792,550</th>
<th>1,294,842</th>
<th>805,430</th>
<th>489,412</th>
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<tbody>
<tr>
<td>R-squared</td>
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<td>0.002</td>
<td>0.002</td>
<td>0.001</td>
<td>0.001</td>
<td>0.013</td>
<td></td>
</tr>
<tr>
<td>Mean Dep. Var</td>
<td>0.603</td>
<td>0.612</td>
<td>0.536</td>
<td>0.283</td>
<td>0.015</td>
<td>0.058</td>
<td></td>
</tr>
</tbody>
</table>

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.7: Aggregate-level decomposition: Heterogeneity for rural-urban areas

<table>
<thead>
<tr>
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<th>(5)</th>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>inc/adult</td>
<td>wage/week</td>
<td>wage/hour</td>
<td>hours/earner</td>
<td>earners/job</td>
<td>job/adult</td>
</tr>
<tr>
<td>Big Storm</td>
<td>-0.080***</td>
<td>-0.038**</td>
<td>-0.020</td>
<td>-0.018*</td>
<td>-0.033</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.016)</td>
<td>(0.012)</td>
<td>(0.009)</td>
<td>(0.021)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Big Storm * city</td>
<td>0.012</td>
<td>0.014</td>
<td>-0.002</td>
<td>0.016</td>
<td>0.012</td>
<td>-0.015</td>
</tr>
<tr>
<td></td>
<td>(0.046)</td>
<td>(0.028)</td>
<td>(0.017)</td>
<td>(0.014)</td>
<td>(0.034)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Small Storm</td>
<td>-0.020*</td>
<td>-0.015**</td>
<td>-0.013**</td>
<td>-0.002</td>
<td>-0.002</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.004)</td>
<td>(0.009)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Small Storm * city</td>
<td>0.026**</td>
<td>0.006</td>
<td>0.005</td>
<td>0.001</td>
<td>0.015</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.008)</td>
<td>(0.007)</td>
<td>(0.005)</td>
<td>(0.010)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Denominator</td>
<td>Adults</td>
<td>Earners</td>
<td>Earned Hours</td>
<td>Earners</td>
<td>Jobs</td>
<td>Adults</td>
</tr>
<tr>
<td>Observations</td>
<td>20,808</td>
<td>20,808</td>
<td>20,808</td>
<td>20,808</td>
<td>20,831</td>
<td>21,064</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.073</td>
<td>0.131</td>
<td>0.146</td>
<td>0.068</td>
<td>0.024</td>
<td>0.016</td>
</tr>
</tbody>
</table>

Note: *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.8: Impacts in levels: Comparison between individual and aggregated results

<table>
<thead>
<tr>
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<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>inc/adult</td>
<td>wage/worker</td>
<td>wage/earner</td>
<td>hours/adult</td>
<td>hours/worker</td>
<td>hours/earner</td>
</tr>
<tr>
<td><strong>Big Storm</strong></td>
<td>-12.796***</td>
<td>-13.102*</td>
<td>-20.872</td>
<td>-0.637**</td>
<td>-0.505</td>
<td>-0.586</td>
</tr>
<tr>
<td></td>
<td>(4.396)</td>
<td>(7.114)</td>
<td>(14.499)</td>
<td>(0.241)</td>
<td>(0.313)</td>
<td>(0.361)</td>
</tr>
<tr>
<td><strong>Small Storm</strong></td>
<td>2.777</td>
<td>9.236*</td>
<td>3.832</td>
<td>-0.164</td>
<td>-0.182</td>
<td>-0.142</td>
</tr>
<tr>
<td></td>
<td>(2.990)</td>
<td>(5.232)</td>
<td>(7.519)</td>
<td>(0.119)</td>
<td>(0.117)</td>
<td>(0.141)</td>
</tr>
<tr>
<td>Observations</td>
<td>21,064</td>
<td>21,064</td>
<td>20,831</td>
<td>21,064</td>
<td>21,064</td>
<td>20,831</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.143</td>
<td>0.149</td>
<td>0.169</td>
<td>0.048</td>
<td>0.052</td>
<td>0.074</td>
</tr>
<tr>
<td>Mean Dep. Var</td>
<td>383.225</td>
<td>700.562</td>
<td>1,280.171</td>
<td>24.139</td>
<td>42.622</td>
<td>43.190</td>
</tr>
<tr>
<td>BStorm as % of Mean</td>
<td>-0.030</td>
<td>-0.024</td>
<td>-0.012</td>
<td>-0.022</td>
<td>-0.014</td>
<td>-0.009</td>
</tr>
</tbody>
</table>

Panel B: Main Impacts in Levels for Individual Data

<table>
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<tr>
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<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>inc/adult</td>
<td>wage/worker</td>
<td>wage/earner</td>
<td>hours/adult</td>
<td>hours/worker</td>
<td>hours/earner</td>
</tr>
<tr>
<td><strong>Big Storm</strong></td>
<td>-11.779**</td>
<td>-11.350</td>
<td>-15.498</td>
<td>-0.619***</td>
<td>-0.609**</td>
<td>-0.564*</td>
</tr>
<tr>
<td></td>
<td>(4.599)</td>
<td>(7.721)</td>
<td>(12.913)</td>
<td>(0.204)</td>
<td>(0.269)</td>
<td>(0.295)</td>
</tr>
<tr>
<td><strong>Small Storm</strong></td>
<td>4.259</td>
<td>11.619***</td>
<td>9.605</td>
<td>-0.137</td>
<td>-0.175</td>
<td>-0.056</td>
</tr>
<tr>
<td></td>
<td>(2.731)</td>
<td>(4.380)</td>
<td>(7.026)</td>
<td>(0.105)</td>
<td>(0.129)</td>
<td>(0.133)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,464,172</td>
<td>1,439,415</td>
<td>669,711</td>
<td>2,464,172</td>
<td>1,453,620</td>
<td>669,711</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.061</td>
<td>0.167</td>
<td>0.174</td>
<td>0.013</td>
<td>0.110</td>
<td>0.072</td>
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<tr>
<td>Mean Dep. Var</td>
<td>391.800</td>
<td>680.000</td>
<td>1,370.700</td>
<td>24.100</td>
<td>41.500</td>
<td>44.700</td>
</tr>
<tr>
<td>BStorm as % of Mean</td>
<td>-0.030</td>
<td>-0.017</td>
<td>-0.011</td>
<td>-0.026</td>
<td>-0.015</td>
<td>-0.013</td>
</tr>
</tbody>
</table>

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.9: Panel-level results: Decomposition for workers who stay at similar jobs

<table>
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<tr>
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<tbody>
<tr>
<td><strong>Panel A:</strong> Impact on Earnings and Hours (Same Job Characteristics)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>wage/week</td>
<td>-0.025**</td>
<td>-0.020**</td>
<td>-0.021**</td>
<td>-0.004</td>
<td>-0.014</td>
<td>-0.008*</td>
</tr>
<tr>
<td>worker</td>
<td>(0.012)</td>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.008)</td>
<td>(0.009)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Big Storm</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small Storm</td>
<td>-0.011*</td>
<td>-0.007</td>
<td>-0.007</td>
<td>-0.004</td>
<td>-0.006</td>
<td>-0.003</td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.003)</td>
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</tr>
<tr>
<td>Sample</td>
<td>Earners</td>
<td>All Earners</td>
<td>Earners</td>
<td>Earners</td>
<td>Earners</td>
<td>Earners</td>
</tr>
<tr>
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<td>157,273</td>
<td>157,962</td>
<td>157,962</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.020</td>
<td>0.005</td>
<td>0.011</td>
<td>0.018</td>
<td>0.014</td>
<td>0.001</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
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<th>(3)</th>
<th>(4)</th>
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<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel B:</strong> Impact on Earnings and Hours (Same Job Characteristics &amp; Payment Type)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>wage/week</td>
<td>-0.027**</td>
<td>-0.021**</td>
<td>-0.021**</td>
<td>-0.006</td>
<td>-0.017*</td>
<td>-0.005</td>
</tr>
<tr>
<td>worker</td>
<td>(0.011)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.008)</td>
<td>(0.009)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Big Storm</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small Storm</td>
<td>-0.011*</td>
<td>-0.003</td>
<td>-0.003</td>
<td>-0.008*</td>
<td>-0.004</td>
<td>0.001</td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>Sample</td>
<td>Earners</td>
<td>All Earners</td>
<td>Earners</td>
<td>Earners</td>
<td>Earners</td>
<td>Earners</td>
</tr>
<tr>
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<td>125,087</td>
<td>125,078</td>
<td>125,087</td>
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<tr>
<td>R-squared</td>
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<td>0.014</td>
<td>0.014</td>
<td>0.020</td>
<td>0.016</td>
<td>0.001</td>
</tr>
</tbody>
</table>

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.