Short and Long-Term Impacts of a Large-Scale Natural Disaster on Individual Labor Outcomes: Evidence from the 2004 Indian Ocean Tsunami

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Abstract

Natural disasters are often highly disruptive to the livelihoods of impacted populations. This paper investigates the effects of the 2004 Indian Ocean tsunami on male wages and labor supply from its immediate aftermath into the long run. Using fixed effects models that account for individual-specific heterogeneity, I find evidence of significant real wage declines for workers from heavily damaged areas that persist beyond the short-term. This long-term wage effect contrasts with previous literature, particularly in the context of relatively less severe disasters. Male workers also increased their hours-of-work following the tsunami, which suggests reliance on labor markets to smooth income losses and shifted their labor towards less disrupted industries. Additionally, I document the heterogeneity of tsunami impact on wages and hours-of-work by birth cohort and education, as well as by industry and sector of employment.

JEL classification: J2; J21; J30; O10; Q54

Keywords: Natural disasters; Local labor markets; Wages; Labor supply

1. Introduction

Due to global warming, environmental degradation and increased population pressures, natural disasters are on the rise across the globe in terms of both frequency and severity. There is a growing body of research documenting the effects of such disasters on various socio-economic outcomes, including aggregate economic growth, asset ownership, health, and inequality (Carter et al., 2007; Frankenberg et al., 2012; Heger & Neumayer, 2019; Yamamura, 2015). However, understanding how labor markets respond to natural disasters is key to understanding how these disasters impact well-being. The labor market is a critical determinant of individual welfare in the face of a disaster, given the close link between wages and consumption especially in post-disaster scenarios when resources are constrained.

Using data from the Study of Tsunami Aftermath and Recovery (STAR), a panel study of individuals from the Indonesian provinces of Aceh and North Sumatra, this paper seeks to explore the immediate and long-term effects of the 2004 Indian Ocean tsunami on wages and labor supply. STAR includes a baseline survey conducted ten months before the tsunami that is representative of the populations living along the coastal regions at risk of being inundated by the tsunami. This population-representative baseline, in conjunction with follow-up surveys of the survivors conducted throughout the subsequent decade, provides rich data that is uniquely suited for this research.

Three salient features distinguish this event from other natural disasters. The first is its immense human and economic cost. In Aceh, the area hardest hit by the tsunami, approximately 5% of the population (over 170,000 people) perished and total damages exceeded 80% of the province’s GDP in the previous year (Masyrafah & McKeon, 2008). Second, the tsunami was completely unexpected. No prior tsunami had struck Sumatra for over 600 years, and there were no early-warning systems in place since tsunamis were not considered to be a risk in the region (Cas et al., 2014). Third, the height and intensity of the tsunami waves depended primarily on idiosyncratic variations in the land topography and undersea bathymetry (Frankenberg et al., 2020). The unanticipated nature of this disaster and the local variations in its severity imply the plausible exogeneity of tsunami exposure from the perspective of individuals and their communities. This stands in stark contrast to other disasters such as earthquakes and tropical storms, where ex ante evacuation and differences in housing quality lead to endogeneity between exposure and unobserved individual characteristics (Kirchberger, 2017; Younes et al., 2021). This paper, in essence, studies how a deeply disruptive, unanticipated, and largely exogenous shock impacts local labor markets.

Natural disasters generally have a downward effect on individual wages in the short-term as capital is destroyed and marginal labor productivity falls (Gignoux & Menendez, 2016; Mueller & Quisumbing 2011). When wages fall, resource-constrained individuals may need to increase their hours-of-work to smooth incomes and avoid large dips in consumption. This labor supply response has been documented in the case of wage shocks attributable to financial crises and crop losses, but a reliance on labor markets to smooth consumption may be less feasible in the context of a highly destructive natural disaster that disrupts labor demand as well (Frankenberg, Smith & Thomas, 2003; Kochar, 1999).

Existing literature has also emphasized substantial heterogeneity in post-disaster labor outcomes, especially by employment characteristics. Labor demand and wages for construction may surge if there is extensive post-disaster rebuilding while agricultural workers could fare poorly if harvests and farm assets are destroyed (Dohrmann et al., 2021; Mueller & Quisumbing, 2011). Older and less educated individuals are also considered less resilient to natural disasters given their limited physical strength and reduced access to resources, but there is a lack of evidence on how these demographic characteristics relate to post-disaster resiliency in terms of labor market outcomes. (Frankenberg et al., 2013; Hutton, 2008).

Additionally, little work has been done on the long-term effects of natural disasters on individual labor outcomes. This constitutes an important gap in the literature as no consensus exists on how natural disasters affect economies in the long run. On one hand, multiple empirical studies claim that disasters hamper economic development and productivity (Hsiang & Jina 2014; Strobl, 2011). On the other hand, disasters may promote growth if the destruction of productive assets stimulates reinvestment and the upgrading of capital stocks (Skidmore & Toya, 2002).

The aim of this paper is to provide scientific evidence that contributes to filling these gaps in the literature. Exploiting the longitudinal nature of STAR, I implement individual fixed-effects models to trace the evolution of wages and labor supply throughout a period spanning ten years post-tsunami. By sweeping out all time-invariant individual characteristics, these fixed effects control for the influence of individual-specific heterogeneity on post-disaster labor outcomes. This approach, when combined with the unanticipated and locally exogenous nature of the tsunami, yields estimates that can be plausibly interpreted as indicative of the causal effects of tsunami exposure on individual labor outcomes into the long run.

I find that although real hourly wages declined for all male workers in the immediate aftermath of the tsunami, the long-term effects of the disaster differed depending on individual exposure to the disaster. Wage losses for those in heavily damaged areas at the time of the disaster persisted throughout the study period whereas workers from other areas quickly recovered and surpassed their pre-disaster earnings. All individuals also worked longer hours post-tsunami, but those outside of heavily damaged areas see greater increases to their work hours.

Beyond these results for all males, I also find evidence of substantial disparities in the tsunami's impact on labor outcomes by both birth cohort and years of schooling as well as by job industry and sector. In general, better-educated and younger individuals experienced stronger wage recoveries and increased their hours of work by more than older and less educated workers. The tsunami was also particularly disruptive towards agriculture and the self-employed sector, while construction wages grew substantially. Given this heterogeneity by industry and sector, I find evidence of workers reallocating their labor away from agriculture and self-employment towards the less disrupted segments of the labor market.

All in all, the key contributions of this paper are as follows. First, using rich longitudinal data collected before and after the tsunami, I provide scientific evidence on the effects of an unanticipated and highly destructive disaster on individual real wages into the long run. Second, I establish that individuals alter their labor supply following this unanticipated shock, by both adjusting the number of hours they work and by reallocating their labor to different sectors and industries. Finally, I document how the post-tsunami evolution of earnings and labor supply are heterogenous across the population by both demographic and employment characteristics.

The rest of this paper is organized in the following manner. Section 2 reviews the existing literature on natural disasters and labor markets. Section 3 describes the STAR study and the data used in this paper. Section 4 discusses the relevant theory that will motivate the empirical models outlined in section 5. I present and discuss the key results in section 6 and section 7 concludes.

2. Literature Review

Scholars have yet to reach a consensus on the effects of natural disasters on the aggregate economy. Instead, existing literature has shown that the relationship between disasters and economic resilience varies depending on both the nature of the disaster (Cavallo et al., 2013; Loayza et al., 2012) as well as the socio-political environment of the impacted region (Noy, 2009). The negative economic effects of highly destructive disasters are more likely to persist into the long-term whereas less severe disasters could promote economic growth. Moreover, wealthier and more developed societies are better equipped to mobilize resources and recover than their less developed counterparts. This heterogeneity suggests that empirical findings from developed nations and moderate intensity disasters may not be generalizable to a middle-income country such as Indonesia recovering from the 2004 tsunami, a highly destructive disaster.

In the case of the 2004 Indian Ocean Tsunami, Heger & Neumayer (2019) compares the post-tsunami GDP of the ten *kabupaten* (districts) of Aceh that experienced coastal flooding to other districts within Sumatra Island and conclude that the damaged districts enjoyed greater long-term economic growth. The study attributes this positive effect to both the extensive post-tsunami reconstruction efforts as well as to a structural reorientation of economic activity in the damaged districts away from agriculture. While these results are informative, their empirical approach does not consider the substantial heterogeneity of tsunami exposure that exists within districts. As each district spans a sizeable area with a large population, the severity of tsunami damage within a given district is not uniform and will vary across communities from non-existent to catastrophic.[1] In contrast to this aggregate analysis, my research examines labor

[1] For example, Aceh Besar, one of the districts in Aceh that experienced coastal flooding, covers 3,000 square kilometers, and had a population of 350,000 in 2010 (Barron et al., 2013).

outcomes at the individual level, and so reflects the true economic consequences of tsunami exposure on those directly impacted.

Most of the literature studying the effects of natural disasters on individual labor outcomes focus on developed countries. In the United States, several papers investigate the effects of hurricanes on individual wages and employment (Deryugina et al., 2018; Dolfman et al., 2007; Groen et al., 2020). They report that while hurricanes negatively impact wages in the short term, these effects largely dissipate within a year. In terms of the heterogeneity of hurricane impact on labor outcomes, these papers generally find that construction wages rise post-disaster due to reconstruction efforts. Further studies show that the labor market consequences of these tropical storms often extend beyond the regions directly impacted, as evacuees and migrants may the lower the wages in nearby areas by flooding the local labor markets elsewhere with excess supply (Belasen & Polachek, 2009; McIntosh, 2008). However, it is unclear to what extent these findings are generalizable to Aceh, in light of the previous discussion. Labor markets in the United States differ significantly from those in Indonesia, where a large segment of the labor force is engaged in agricultural production or are self-employed in small family enterprises (Rosenzweig, 1988).

In contrast, Gignoux & Menendez (2016) and Mueller & Quisumbing (2011) study the effects of disasters on labor outcomes in environments more similar to Aceh. Using a panel of male workers from Indonesia, but not including Aceh, Gignoux & Menendez (2016) implement individual fixed effects models to study the effects of earthquake exposure on individual wages. They find that, in the short-term, agricultural wages experienced larger declines than off-farm wages, but by the sixth year following an earthquake, both agricultural and non-agricultural wages have recovered and experienced growth. While this study provides some evidence that disasters may have positive long-term impacts on individual wages, most of the earthquakes in their sample are of moderate intensity, and thus are not comparable to the highly destructive 2004 tsunami. Additionally, they do not examine how earthquakes affect labor supply or investigate the heterogeneity of earthquake impact on wages by demographic characteristics.

Mueller & Quisumbing (2011) examine the effects of the 1998 floods in Bangladesh on individual labor outcomes and find that wages declined in the short term but generally recovered by the fifth year post-flood. Like Gignoux & Menendez (2016), Mueller & Quisumbing report that agricultural wages experienced greater short-term declines than off-farm wages. However, two aspects of the 1998 Bangladesh floods limit the comparability of that disaster to the 2004 tsunami. First, the death toll was relatively minimal (Del Ninno et al., 2001). Second, floods in Bangladesh are seasonal and likely anticipated, so individuals may adopt a variety of ex ante risk-coping strategies such as through insurance or income diversification (Rose, 2001). Unlike STAR, their panel was also formed in the aftermath of the floods and thus may not be representative of the impacted population since individuals often migrate post-disaster (Frankenberg et al., 2016).

Following a natural disaster, individuals may alter their labor supply by reallocating their labor towards more productive sectors, particularly if the impact of such a disaster is heterogeneous across different segments of the labor market. Multiple studies have found that agricultural households will shift their labor towards off-farm employment during periods of weather-induced crop losses (Cameron & Worswick, 2003; Kijima et al., 2006; Kochar, 1999). Additionally, in the case of the 2004 Indian Ocean, Nose (2019) provides evidence of fishermen in Aceh who had lost their productive assets to the 2004 tsunami transitioning to alternate forms of employment.

Existing literature on consumption smoothing suggests that workers may increase their hours in response to a negative wage shock, especially if other avenues of consumption smoothing are unavailable. This labor supply response has been documented in the case of the 1997 Asian Financial Crisis when credit markets were constrained (Frankenberg, Thomas & Smith, 2003) as well as for the poorest households, who are less able to minimize dips in consumption by other means (Blundell et al., 2016; Jayachandran, 2006; Sharif, 1991). However, the evidence for any hours of work increases following a natural disaster is mixed (Jiminez Martinez et al., 2020; Kirchberger 2017). Mueller & Quisumbing (2011) finds no significant changes to individual work hours, except for casual workers in agriculture who worked longer hours one year after the floods. One explanation for this lack of evidence is that disasters negatively impact labor demand as well. Firms may reduce labor inputs post-disaster, thereby limiting opportunities for workers to increase their labor supply (Franklin & Labonne, 2017).

Finally, a growing body of literature has been devoted to identifying the population subgroups whose welfare are most negatively impacted by disasters (Frankenberg et al., 2013; Tierney, 2007). From this strand of research, age and education have emerged as dimensions by which individual resiliency to disasters can vary. Older individuals are at greater risk of death or injury, given their relative physical weakness, and are also less likely to have their needs met post-disaster (Frankenberg et al., 2016; Hutton 2008; Ngo, 2001). On the other hand, highly educated individuals generally possess greater social and financial resources which may facilitate a faster and more robust recovery following natural disasters. In the context of the 2004 tsunami, better educated individuals were less likely to relocate to a refugee camp and also exhibited lower levels of post-traumatic stress five years after the event (Frankenberg et al., 2013).

However, research is scarce on how the labor market consequences of natural disasters vary as function of an individual's age or education.

3. DATA

STAR Overview

This paper uses data from the Study of Tsunami Aftermath and Recovery (STAR) study. STAR is an ongoing panel survey of individuals living along the coastlines of Aceh and North Sumatra. Fielded for the specific purpose of investigating the socio-economic effects of the 2004 Indian Ocean Tsunami, the survey involves over 28,000 respondents in 7,000 households and includes a detailed labor module that records each individual's employment status and earnings. In the STAR study, baseline information is provided by a population-representative sample that was interviewed ten months before the tsunami. This pre-disaster baseline was conducted by Statistics Indonesia as part of the 2004 National Socio-Economic Survey (SUSENAS) and was designed to be population-representative at the district level. STAR follows all SUSENAS respondents who, at the time of the tsunami, were living in coastal districts at risk of being flooded and who survived the disaster. This yields a sample covering eleven districts in Aceh province and two additional districts in neighboring North Sumatra. All individuals in the sample were tracked in multiple follow-up interviews conducted annually for the first five years post-tsunami and once again ten years post-tsunami in 2015.

The estimation sample for this paper consists of all male respondents in STAR aged between twenty to sixty at the pre-tsunami baseline. I restrict my analysis to only males to avoid potential issues arising from incomplete labor force participation. Less than half of working-age female respondents in STAR were employed in any given STAR wave. This low rate of female participation means first, that data on female earnings is limited, and second, that any empirical analysis involving female labor outcomes will need to control for self-selection into employment. Thus, although female labor outcomes represent an important facet of individual well-being, this area of inquiry is left to future work.

Attrition

Non-random attrition may lead to biased results in longitudinal studies. This is particularly true for panel studies in developing countries where incomplete communications infrastructure makes it difficult to track down migrants and even more so in the context of a disaster since large segments of the population may indeed relocate post-disaster (Thomas et al., 2001). In light of this issue, particular effort was devoted in STAR to tracking down and re-interviewing all surviving SUSENAS respondents, including those who migrated to other provinces or countries. Of the 6,371 males in the estimation sample, 96.1% were reinterviewed at-least once post-tsunami and over 88.1% were tracked down in the ten year follow-up.

Relevant Variables

Tsunami Exposure

I classify each respondent into tsunami exposure groups depending on the community that they were residing in at the time of the disaster. More specifically, every individual in STAR belongs to an enumeration area (EA), which is a cluster of 16 households in close geographic proximity that were sampled together in the pre-tsunami baseline.[2] The extent of tsunami damage for each EA is determined primarily through satellite imagery taken by NASA's Moderate Resolution Imaging Spectroradiometer (MODIS). The team behind STAR compares satellite imagery of a 0.6 kilometer-squared region centered at each EA taken nine days prior to the tsunami to an image of the same area taken three days after and measures the proportion of land

[2] For the remainder of this paper, I will use the terms "community" and "enumeration area" interchangeably.

cover that transformed into bare earth (Frankenberg et al., 2013). This metric is used to classify each enumeration area as either suffering no damage, moderate damage, or heavy damage.

I group the males from heavily damaged EAs at the pre-tsunami baseline into the heavy exposure group and designate the rest as the other exposure group. I emphasize this distinction because mortality was heavily concentrated in the communities classified as heavily damaged. 26.7% of all SUSENAS baseline respondents from heavily damaged EAs perished by the first post-tsunami follow-up whereas this mortality rate for respondents in moderately damaged and undamaged EAs is only 2.8% and 2.6% respectively. Respondents from heavily damaged areas were also substantially more likely to lose family members to the tsunami, to suffer property damage, and to experience elevated levels of post-traumatic stress following the disaster (Frankenberg et al., 2008, 2016).

Labor Supply and Type of Employment

The labor module in STAR asks each respondent whether they engaged in work the previous week. Conditional on employment, each respondent is subsequently asked how many hours they work in a normal week.

Employed respondents are also asked if they (1) hold a permanent job with a formal contract, (2) are a casual day laborer, (3) are self-employed or (4) are engaged in unpaid work with the family. I classify (1) and (2) as the market wage sector and group (3) and (4) as the self-employed sector. The primary distinction here is between the workers who are paid a wage for their labor and those whose earnings are determined by the profitability of their own enterprise.

Those who work are additionally asked to describe in writing the industry that best describes their institution of work. Based on this answer, the STAR interviewer then assigns the respondent a three-digit code from Indonesia's Business Field Standard Classification system. I use this three-digit industrial code to classify each worker as being employed in either agriculture, construction, or other non-construction off-farm industries.

Earnings

Each employed respondent in STAR reports the earnings from their primary job in the previous month. To compute hourly wages, I divide each respondent's monthly earnings by the quantity of their weekly work hours multiplied by 4.35. One limitation of the STAR data is that the labor module in the pre-tsunami baseline survey only records the monthly earnings for permanent job workers. However, the one-year post-tsunami follow-up asks all employed individuals to recall their work-related earnings in the previous (2004) calendar year. To maintain consistency between the permanent job holders and other workers, I rely on retrospective earnings to measure the pre-tsunami wages of all individuals.

Prices

All earnings reported in STAR are expressed in nominal terms in thousands of *rupiah*, the Indonesian currency. To derive the real wages for each worker, I deflate their nominal earnings with a consumer price index computed using prices and household consumption data from STAR. This price index is disaggregated by *kecamatan* (sub-district) and community damage level to capture any post-tsunami spatial variations in prices. In particular, the price level for a particular sub-district and damage level is defined as the weighted average of all goods and services prices from the relevant communities where the weights are the median household consumption shares of each expenditure category.[3] I then standardize all reported wages to

[3] My methodology in constructing the price index closely follows the approach taken in Lawton (2020). See that paper for additional details.

reflect the average purchasing power of a 2005 *rupiah* in undamaged communities within the Banda Aceh district.

Age and Education

In STAR, each respondent reports their age and years of schooling. Using these demographic variables, I divide the estimation sample into the young (aged 20 to 30 prior to the tsunami), middle (aged 30 to 40), or older (aged 40 to 60) birth cohorts based on each individual's age at the time of the tsunami. Additionally, each individual is also grouped into the primary-level (0 to 6 years of schooling prior to the tsunami), secondary-level (7 to 12 years of schooling), or college-level (13+ years of schooling) education cohorts depending on their years of schooling at the pre-tsunami baseline.

Summary Statistics

Descriptive statistics for the estimation sample at the pre-tsunami baseline are reported in Table 1. Of the 6,371 males that comprise the sample, 1,309 belong to the heavy exposure group whereas the remaining 5,062 form the other exposure group. Approximately 88.8% males were working before the tsunami and amongst the employed, 54.2% were in agriculture while 66.2% were self-employed. In terms of the demographic characteristics, 64.0% of respondents in the sample were under the age of 40 at the time of the tsunami, and only 8.0% were educated at the college level.

Table 1: Pre-Tsunami Descriptive Statistics for the Estimation Sample

Variables	(1)
Birth Cohort (Proportion of Sample)	
20-30 years	0.332
30-40 years	0.308
40-60 years	0.360
Education Cohort (Proportion of Sample)	
0-6 years	0.374
6-12 years	0.546
12+ years	0.080
Employment	0.888
Work Hours per Week	42.79
Real Monthly Earnings (000s Rp)	1001.9
Real Hourly Wages (000s Rp)	5.821
Log Real Hourly Wages	1.612
Sector (Proportion of Employed)	
Market Sector	0.338
Self-employed	0.662
Industry (Proportion of Employed)	
Agriculture	0.542
Construction	0.067
Other Off-farm	0.391
Number of Individuals	
Heavy	1,309
Other	5,062
Total	6,371

4. Theoretical Framework

In this section, I will outline a model of labor supply whereby an individual sets their hours of work depending on their hourly wage, asset ownership, expectations regarding the future, among other characteristics. The model described here closely follows the life cycle labor supply models applied in MaCurdy (1981), Cameron & Worswick (2003), and Lawton (2020). Additionally, I will discuss the channels through which a natural disaster affects wages and how this impact varies across the population. The insights from this section will inform my empirical analysis that constitutes the remainder of this paper.

Labor Supply Model

Consider an individual whose lifetime consists of *T* discrete time periods and whose preferences over leisure and consumption are shaped by the parameter α. At each time period *t*, the individual devotes *M* total hours to either leisure, *L(t)*, or labor, and additionally consumes *C(t)* to maximize the present discount value of his expected lifetime utility:

$$U(C(t), L(t), \alpha) + \mathbb{E}_t\left[\sum_{\tau=t+1}^{T}(1+\delta)^{-\tau+t}U(C(\tau), L(\tau), \alpha)\right] \quad [1]$$

where δ is the rate of time preference. The individual solves this utility maximization problem subject to a period-specific time constraint on leisure:

$$L(t) \leq M \text{ for each } t = 1, 2, \ldots T \quad [2]$$

as well as a savings constraint:

$$A(t) - (1 + r(t))A(t-1) = w(t)h(t) - C(t) + \gamma(t) \text{ for each } t = 1, 2 \ldots T \text{ and } A(T) \geq 0 \quad [3]$$

where $A(t)$ is the real value of any assets or debts at the beginning of period t, $r(t)$ is the rate of saving and borrowing, $h(t) = M - L(t)$ is the number of hours devoted to labor, $w(t)$ is the real hourly wage, and $\gamma(t)$ represents other idiosyncratic shocks to assets. $\gamma(t)$ could be negative, if, for example, an individual incurred asset losses from the tsunami, or positive, if the individual was a recipient of aid. This savings constraint sets the left-hand side, which represents the change in the individual's real assets during period t, equal to their labor market earnings net consumption and other asset shocks in that period. Additionally, the individual must clear all debts at the end of their life: $A(T) \geq 0$.

Solving this utility maximization problem yields a period-specific labor supply function that varies depending on assets at beginning of lifecycle, $A(0)$, rate of time preference δ, personal preferences over leisure and consumption α, as well as vectors for the present and expected future values of wages, $\boldsymbol{w(t)}$, interest rates, $\boldsymbol{r(t)}$, and other asset shocks, $\boldsymbol{\gamma(t)}$:

$$h(t) = h(\boldsymbol{w(t)}, \boldsymbol{r(t)}, \boldsymbol{\gamma(t)}, A(0), \delta, \alpha) \quad [4]$$

This paper seeks to empirically document the evolution of post-tsunami hours of work, $h(t)$ and hourly wages $w(t)$ from the immediate aftermath of the disaster into the long run. Since I only consider working-age males, each individual is assumed to arrive at an interior non-zero solution for their labor supply at every period. Any non-participation will be treated as idiosyncratic missing data.

In this model, an individual will adjust their work hours following a disaster depending on how their wage changes, while factoring in additional parameters such as their future expected wages and owned assets. Suppose wages fall for a certain worker in the aftermath of a disaster. This shock generates a wealth effect, whereby labor supply increases to partially offset the losses in earnings, and a substitution effect, where the individual increases their leisure demand given its lower opportunity cost. The relative sizes of these effects depend on the individual's ability to smooth consumption via non-labor mechanisms such as by borrowing or selling off assets, as well as on expectations regarding future wages. Individuals who are credit constrained or with low savings may need to increase their hours of work in response to the wage shock to avoid large dips in consumption (Frankenberg, Thomas & Smith, 2003). Additionally, those who expect their wages to remain depressed into the future may work longer hours as they would be less inclined to engage in intertemporal substitution of leisure (MaCurdy, 1981). In short, the labor supply response to a given disaster-induced wage shock varies across individuals as a function of age and education and other characteristics that determine post-disaster asset ownership, accessibility of credit, and expectations regarding the future.

Heterogeneity in Disaster Impact on Wages

While the factors described above contribute significantly to heterogeneity in individual post-disaster labor supply responses, the size and duration of the wage shock itself also differs across the population. A key dimension by which a disaster's impact on wages can vary is the worker's sector and industry of employment. Earnings for those self-employed in family enterprises are directly determined by the profitability of their business (Strauss & Thomas, 1995). As a disaster degrades infrastructure and destroys capital stocks, their earnings and profits will deteriorate. In the context of the 2004 tsunami, agricultural family businesses may be particularly vulnerable as coastal flooding damaged agricultural equipment, destroyed rice harvests and inundated fields with saltwater (Griffin et al., 2013; Nose, 2019; Thorbunn, 2009).

In contrast, the wages of market sector workers are jointly determined by the interactions between labor supply and demand. Destruction to infrastructure will unambiguously reduce labor demand by hindering access to markets, while the effects of capital losses on labor demand will depend on the degree of substitutability between labor and capital (Kirchberger 2017; Jiminez Martinez et al., 2020). Firms may react to a reduction in capital by reducing the labor they hire, or by increasing their labor demand to maintain production. Whether labor and capital act as complements or substitutes depends on the firm-specific production function and is likely also heterogeneous across industries. Post-disaster reconstruction efforts may also increase labor demand for certain jobs, especially in construction. In terms of labor supply, deaths, injuries, and migrations may reduce the availability of labor in directly affected areas, thereby exerting an upward pressure on wages. Thus, the movement of market sector wages is less clear *a priori* and likely highly variable across industries.

Beyond this wage shock heterogeneity by type of employment, workers may switch jobs or migrate in search of higher wages post-disaster (Cameron & Worswick, 2003; Deryugina et al., 2018; Kochar, 1999). These behaviors are not costless and are endogenous to various characteristics such as socio-economic status, degree of risk-aversion and physical fitness. In addition to migration and employment transitions, the replacement of destroyed capital is also critical to wage recovery, particularly for the self-employed (Nose, 2019). However, the ability to restore lost assets depends on factors such as pre-disaster socio-economic status or access to credit. Wealthy self-employed workers may quickly recover their business assets and earnings while their peers who are worse off prior to the disaster could be permanently trapped in vicious cycles of low productivity (Carter et al., 2007). All in all, the size and persistence of a disaster's impact on wages varies between individuals by both the industry and sector of employment as well as by the various characteristics that influence behaviors such as job switching or migration.

5. Empirical Specification

Empirical Strategy

The primary empirical objective of this paper is to document the causal impact of tsunami exposure on wages, *w(t)*, and hours of work, *h(t)*, from its immediate aftermath into the long run. But as discussed in the theoretical framework, the trajectories of post-disaster wages and labor supply are influenced by a slew of individual-specific factors beyond the disaster itself. In particular, the size and duration of the wage shock varies by both the individual's type of employment, as well as by potential post-disaster behaviors that include migration, job switching, and replacing lost capital. Workers then set their labor supply based on their current wages, their personal preferences over leisure and consumption, capacity of smooth consumption through non-labor mechanisms, and their expectations regarding future wages. Without controlling for these characteristics and behavioral responses, the post-disaster trajectories of labor outcomes are difficult to interpret and cannot be considered as indicative of the causal impact of the tsunami.

My empirical strategy, given the theoretical considerations highlighted above, is to exploit the longitudinal nature of the STAR study and adopt an individual fixed-effects approach. These fixed effects control for all individual characteristics influencing post-tsunami wages and labor supply to the extent that they are fixed over time, including factors that are otherwise difficult to measure such as willingness to adapt or innate ability. More specifically, I estimate the following model on the entire estimation sample:

$$y_{ijt} = \boldsymbol{z}'\boldsymbol{\beta}_1 + D_j \cdot \boldsymbol{z}'\boldsymbol{\beta}_2 + \mu_{ij} + \tau_{ijt} + \epsilon_{ijt} \quad [5]$$

for individual *i* from community *j* observed in year *t*. Here, the dependent variable *y* represents either log real hourly wages or hours worked per week, ***z*** is a vector of six indicators each corresponding to one of the STAR follow-up waves conducted annually for the first five years post-tsunami and once more ten years afterwards, D is an individual-specific indicator that takes on the value of one if that person was living in a heavily damaged community at the time of the tsunami and zero otherwise, and μ is the individual fixed effect. I also include a month-of-interview fixed effect, τ, to account for any variations in hours of work or wages attributable to seasonal fluctuations. In this model, the vector $\boldsymbol{\beta}_1$ traces out the evolution of the outcome variable for males in the other exposure group relative to their excluded pre-tsunami baseline while $\boldsymbol{\beta}_1+\boldsymbol{\beta}_2$ identifies the outcome trajectory of those in the heavy exposure group. All standard errors are to be heteroskedasticity-robust and clustered at the community level.

Beyond the identification of post-tsunami labor outcome trajectories for all males, the other objective of this paper is to document the heterogeneity of tsunami impact by age and education, as well as by employment sector and industry. To this end, I extend model [5] by interacting both the ***z*** and *D*·***z*** terms with indicators corresponding to membership in the middle and older birth cohorts:

$$y_{ijt} = \boldsymbol{z}'\boldsymbol{\beta}_1 + D_j \cdot \boldsymbol{z}'\boldsymbol{\beta}_2 + \mathbb{1}[mid]_{ij} \cdot \boldsymbol{z}'\boldsymbol{\beta}_3 + D_j \cdot \mathbb{1}[mid]_{ij} \cdot \boldsymbol{z}'\boldsymbol{\beta}_4 + \mathbb{1}[old]_{ij} \cdot \boldsymbol{z}'\boldsymbol{\beta}_5 + D_j \cdot \mathbb{1}[old]_{ij} \cdot \boldsymbol{z}'\boldsymbol{\beta}_6 + \mu_{ij} + \tau_{ijt} + \epsilon_{ijt} \quad [6]$$

and with indicators corresponding to membership in the secondary-level and college-level education cohorts:

$$y_{ijt} = \boldsymbol{z}'\boldsymbol{\beta}_1 + D_j \cdot \boldsymbol{z}'\boldsymbol{\beta}_2 + \mathbb{1}[sec]_{ij} \cdot \boldsymbol{z}'\boldsymbol{\beta}_3 + D_j \cdot \mathbb{1}[sec]_{ij} \cdot \boldsymbol{z}'\boldsymbol{\beta}_4 + \mathbb{1}[coll]_{ij} \cdot \boldsymbol{z}'\boldsymbol{\beta}_5 + D_j \cdot \mathbb{1}[coll]_{ij} \cdot \boldsymbol{z}'\boldsymbol{\beta}_6 + \mu_{ij} + \tau_{ijt} + \epsilon_{ijt} \quad [7]$$

To document how post-tsunami labor outcomes vary by industry and sector, I again extend model [5] with indicators that correspond to employment in construction and other off-farm industries:

$$y_{ijt} = \boldsymbol{z}'\boldsymbol{\beta}_1 + D_j \cdot \boldsymbol{z}'\boldsymbol{\beta}_2 + \mathbb{1}[cons]_{ijt} \cdot \boldsymbol{z}'\boldsymbol{\beta}_3 + D_j \cdot \mathbb{1}[cons]_{ijt} \cdot \boldsymbol{z}'\boldsymbol{\beta}_4 + \mathbb{1}[other]_{ijt} \cdot \boldsymbol{z}'\boldsymbol{\beta}_5 + D_j \cdot \mathbb{1}[other]_{ijt} \cdot \boldsymbol{z}'\boldsymbol{\beta}_6 + \mu_{ij} + \tau_{ijt} + \epsilon_{ijt} \quad [8]$$

as well as with an indicator that differentiates between employment in the market and self-employed sectors:

$$y_{ijt} = \boldsymbol{z}'\boldsymbol{\beta}_1 + D_j \cdot \boldsymbol{z}'\boldsymbol{\beta}_2 + \mathbb{1}[self]_{ijt} \cdot \boldsymbol{z}'\boldsymbol{\beta}_3 + D_j \cdot \mathbb{1}[self]_{ijt} \cdot \boldsymbol{z}'\boldsymbol{\beta}_4 + \mu_{ij} + \tau_{ijt} + \epsilon_{ijt} \quad [9]$$

Unlike with birth or education cohorts, the indicators for sector and industry are time-varying for each individual as workers may transition between types of employment over the course of the study period. While these transitions are likely endogenous, the individual fixed effects control for self-selection into each industry or sector to the extent that the factors influencing job-switching behavior, such as willingness to adapt or degree of risk aversion, are fixed over time. To complement this analysis, I also document the individual transitions across job types by estimating model [5] on indicator variables that take on the value of one if the individual is employed in a particular industry or sector, and zero for employment elsewhere.

Conditional Exogeneity of Tsunami Exposure

In each of the models specified above, the post-tsunami evolution of labor outcomes is identified separately by exposure group. For the comparison of trajectories between the exposure groups to be causal, any heterogeneity between the heavy and other groups needs to be controlled for. The individual fixed effects terms in each model already account for all arbitrary differences across exposure groups to the extent that the effects of this heterogeneity on labor outcomes are fixed over time and additively separable from the effects of tsunami exposure.

However, these functional form and time-invariance requirements are not necessary if I can treat tsunami exposure as exogenous conditional on certain pre-tsunami characteristics. Before proceeding onwards to the empirical results, I shall examine this assumption in greater detail.

Table 2: Pre-Tsunami Labor Outcomes Stratified by Exposure Group

			Difference	
Variables	Heavy (1)	Other (2)	Unadjusted (3)	Adjusted (4)
Employment	0.848	0.897	-0.049**	-0.032
			(0.018)	(0.023)
Weekly Hours	45.953	42.003	3.950***	1.691
			(1.120)	(1.173)
Log Real Hourly Wages	1.504	1.140	0.365***	0.166
			(0.071)	(0.087)
Sector (Proportion of Employed)				
Market Sector	0.339	0.338	0.001	0.001
			(0.035)	(0.036)
Self-Employed	0.661	0.662	-0.001	-0.001
			(0.035)	(0.036)
Industry (Proportion of Employed)				
Agriculture	0.423	0.571	-0.148***	-0.095*
			(0.045)	(0.045)
Construction	0.077	0.065	0.013	0.000
			(0.014)	(0.017)
Other Off-farm	0.500	0.365	0.135***	0.095*
			(0.040)	(0.048)
# of Individuals	1,309	5,062		

Adjusted difference includes controls for age, distance of EA to coast and sub-district fixed effects
Heteroskedasticity robust standard errors in parentheses, clustered at the EA-level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2 presents pre-tsunami labor outcomes stratified between the heavy (Column 1) and other exposure groups (Column 2). From Column 3, which reports the unadjusted differences of each labor outcome across the exposure groups, it is clear that these groups were not interchangeable prior to the tsunami. Males in the heavily damaged areas were significantly less likely to be employed, worked longer hours, earned higher wages, and were more likely to be employed in non-agricultural industries relative their peers in other areas.

Two factors likely contribute to these differences in labor outcomes across the exposure groups. First, Banda Aceh, the capital city of Aceh province, sustained enormous damage so areas of heavy damage tended to be more developed and urban on average prior to the tsunami. Second, prime age and physically fit individuals were more likely to survive the tsunami than the old or infirm (Frankenberg et al., 2011). This survival selection could increase the disparities observed in wages and hours of work if characteristics beneficial to survival, such as physical fitness, also correspond to increased productivity and work hours. Therefore, tsunami exposure may be exogenous to labor outcomes after survival selection and differences across regions are accounted for.

To test this hypothesis, Column 4 of Table 2 reports the differences in labor outcomes controlling for sub-district, the distance of the individual's community to the coastline, and age, which I use as a proxy for fitness. With the inclusion of these controls, the disparities in employment rate, weekly work hours, and log hourly wages all shrink to the point of statistical insignificance. Likewise, the difference in the proportion of workers employed in agriculture shrinks from 14.8 percentage points to 9.5 p.p., although this adjusted difference remains statistically significant at the 5% level. Overall, these findings indicate that a large part, albeit not all, of the heterogeneity in pre-tsunami labor outcomes between the exposure groups are attributable to variations across regions or to age differences. While the conditional exogeneity of exposure is not required for a causal interpretation of the comparison terms in the empirical models, this finding nonetheless adds an additional layer of robustness to my results.

6. Results and Discussion

Primary Results

Log Real Wages

The post-tsunami trajectories of log real hourly wages are presented in Table 3. Columns 2 and 3 correspond to the estimated coefficients $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ from model [5] respectively. For the sake of clarity, I also report $\boldsymbol{\beta_1+\beta_2}$, the wage trajectory for the heavy exposure group, directly in Column 1.[4] Pre-tsunami wage levels for the heavy and other exposure groups, as well as the size and statistical significance of the difference, are listed under the *Pre-tsunami* panel.[5]

Prior to the tsunami, males from heavily damaged areas earned approximately 36.5% higher real hourly wages compared to their peers in other areas.[6] Yet in the immediate aftermath of the disaster, wages declined dramatically for workers in both exposure groups. Those residing in heavily damaged communities at the time of the tsunami experienced a 32.1% wage decline whereas wages for their peers in the other exposure group also fell by 21.8%. Several channels may explain the spillover wage effect felt by individuals living outside of the immediate areas where capital and infrastructure were damaged. First, migratory outflows away from devastated areas may flood the local labor markets of nearby areas with excess labor supply, thus lowering wages. This mechanism has been well-documented in the case of tropical storms in the US and prior research using STAR data suggests that over 60% of adults in heavily damaged areas moved from their homes post-tsunami (Gray et al., 2014). General equilibrium effects may also

[4] Standard errors for the $\boldsymbol{\beta_1+\beta_2}$ coefficients are calculated by re-estimating model [5] but with the exposure indicator *D* flipped, taking on the value of 1 if the individual belongs to the other exposure group and 0 otherwise.
[5] Pre-tsunami wage levels and their difference are computed separately and are not from model [5]. This is because, in model [5], the pre-tsunami values of the outcome variable get absorbed into the fixed effects.
[6] Throughout this paper, I will report the differences in log wages as percentages. This is an approximation, but the error is minimal, especially for small changes.

contribute to the observed spillovers. If the local economies were well-integrated, then the economic shock to heavily damaged areas likely caused ripple effects elsewhere through disruptions to trade or demand for goods, thereby lowering wages in nearby regions as well.

However, over the next ten years, wages for the heavy and other exposure groups followed very different trajectories. On one hand, real wages for those in indirectly affected or undamaged areas at the time of the tsunami surpassed pre-tsunami levels in the third year and eventually rose to 14.1% above their pre-tsunami wage levels. On the other hand, wages for the heavy exposure group did not recover pre-tsunami levels and remained 7.3% below baseline even in the tenth year. The differences estimates presented in Column 3 confirm this disparity in long-term wage trajectories. In the immediate aftermath of the tsunami, there was a 10.3 p.p. difference in wage changes across the two groups, but this difference widened to 21.4 p.p. by the third year and remained above 20 p.p. for the rest of the study period.

The long-term wage losses experienced by those in the heavy exposure group contrasts with the results of Gignoux & Menendez (2016) and Mueller & Quisumbing (2011) who, studying mostly moderate intensity earthquakes in Indonesia and the 1998 Bangladesh floods respectively, report only transitory wage disruptions. The evidence presented here suggests that while labor markets may be more resilient towards medium severity disasters, the extensive destruction to capital and infrastructure from catastrophic disasters like the 2004 tsunami have long-term consequences, at least for labor outcomes.

Before the tsunami, workers in other regions earned significantly lower wages than their peers in communities that would be heavily damaged. Yet, this gap narrowed after the tsunami as workers from the other exposure group recovered and experienced wage growth. One explanation for this convergence is that workers in other areas also benefited from post-tsunami reconstruction efforts, which may have stimulated investment in communities that, while not directly impacted by the tsunami, possessed low levels of productive capital. Migration could be another factor. Beyond the relocation of individuals away from heavily damaged areas discussed previously, workers in low wage communities at the time of the tsunami may have also migrated elsewhere in search of better employment opportunities. In either case, my results add a layer of nuance to the conclusions of Heger & Neumayer (2019), who report greater GDP growth in the districts of Aceh affected by the tsunami. This economic resurgence, while potentially reflected in the wage growth experienced by those residing outside of heavily damaged areas, is not shared by the individuals directly affected by the tsunami, at least in terms of their labor market earnings.

Hours of Work

The trajectories of weekly work hours are reported in Table 4. Prior to the tsunami, males from the heavy exposure group worked 3.95 more hours per week than their peers in the other exposure group. Subsequently, males from both exposure groups increased their work hours throughout the first few years post-tsunami, even in the face of the previously discussed wage declines. Individuals in the other exposure group spent 4.31 more hours on work in the first year post-tsunami than at baseline (Column 2) while the weekly hours for those in the heavy exposure group also peaked at 2.97 hours above their pre-tsunami levels in the third year (Column 3). These estimates indicate that, at least in the short-term, the income effect of the tsunami-induced wage loss dominated the substitution effect and so workers in both exposure groups increased their work hours after the tsunami to mitigate income losses.

These labor supply responses did partially reverse in the long run. By the end of the study period, males in the heavy group worked 0.54 hours less per week compared to baseline while those in other communities only worked 2.77 hours more than their pre-tsunami levels.

Despite experiencing greater wage disruptions, males in the heavy exposure group did not increase their post-tsunami work hours by as much as their peers in other communities (Column 3). One explanation for this disparity is that damage to capital and infrastructure reduced labor demand in heavily damaged communities and therefore limited the opportunity of those in the heavy exposure group to provide more labor. Alternatively, external aid could have partially offset the wage declines for the heavy group and thus reduced the need for consumption smoothing through the labor market. Validating these hypotheses would require an analysis of post-tsunami labor outcomes that factors external aid and labor demand into consideration. Such an approach, while potentially promising, is beyond the scope of the present paper.

Labor Outcome Heterogeneity by Birth and Education Cohorts

With the primary results now established, we next turn our attention to how the post-tsunami trajectories of outcomes differed across various population subgroups. Here, I explore post-tsunami heterogeneity in labor outcomes by birth cohort and by years of education at the time of the tsunami.

Birth Cohort

Table 5 presents the post-tsunami log real hourly wages trajectories differentiated by the young (aged 20 to 30 at the time of the tsunami), middle (aged 30 to 40), and older (aged 40 to 60) birth cohorts. All results in the table are from model [6], but for the sake of readability, I directly report the wage trajectories of the middle and older cohorts, rather than present the differences of their post-tsunami wage changes relative to the excluded young cohort.[7]

In the immediate aftermath of the tsunami, the young cohort in the heavy and other exposure groups experienced real wage declines of 13.3% and 20.0% respectively (Table 5, Columns 1-2). Young workers in both exposure groups subsequently recovered and earned wages 13.8% and 26.7% above their pre-tsunami levels by the tenth year. Although young workers in other areas outperformed their peers in the heavy exposure group in terms of wage recovery, the differences in their post-tsunami wage changes are never statistically significant (Column 3). In contrast, the middle cohort in the heavy and other exposure groups experienced wage declines of 36.8% and 21.3% in the first year (Columns 4-5). By the end of the study period, wages for the middle-cohort in the other group had risen to 16.9% above their pre-tsunami levels but wages for their peers in the heavy exposure group remained 4.6% below baseline. Unlike with the young cohort, this 21.5 p.p. difference in tenth year wage changes is significant at the 5% level (Column 6). For older workers, the differences in wage trajectories across the exposure groups are even larger. While the older cohort in the other group had recovered to their pre-tsunami earnings by the third year, the wages for their peers in the heavy group never recovered and remained nearly 20% below baseline throughout the entire study period (Columns 7-9).

In terms of hours of work, all three birth cohorts worked longer hours post-tsunami, especially in the short run (Table 6).[8] However, for both exposure groups, these labor supply

[7] Standard errors for the post-tsunami wage changes of the middle and older cohorts are computed by re-estimating model [6] but with the middle and older cohorts set as the excluded subgroup, respectively.
[8] All tables documenting the heterogeneity in post-tsunami wages and work hours follow Table 5 in format, and present the trajectories directly for each subgroup, rather than report differences relative to some excluded subgroup.

increases were largest for the young cohort. Among those residing in other areas at the time of the tsunami, younger workers spent 5.42 more hours working per week in the second year (Column 2) whereas work hours for the middle and older cohorts only peaked at 4.73 and 3.39 hours above their respective pre-tsunami levels (Columns 5 & 8). Similarly, the young cohort in the heavy exposure group increased their work hours by 4.53 in the third year (Column 1) while their peers in the middle and older cohorts only worked, at most, 2.55 and 2.77 more hours respectively compared to before the tsunami (Columns 4 & 7).

Overall, these results indicate that, especially for those living in heavily damaged communities at the time of the tsunami, older workers did not fare as well in terms of their labor outcomes. This finding corroborates prior research that identifies age as a characteristic negatively correlated with post-disaster resiliency and well-being. Older workers from devastated communities not only experienced large wage losses that persisted into the long run, but also did not increase their hours-of-work by as much as their younger peers. While the number of hours each individual devotes to work does not, in itself, have a clear interpretation in terms of well-being, the evidence nonetheless shows that older workers were either less willing or less able to rely on labor supply adjustments to smooth over income losses. These disparities by age could arise if older workers were not as adaptable or physically fit, and thus were less able to take advantage of new opportunities by switching jobs or migrating.

Education Cohort

Table 7 presents the post-tsunami log real hourly wages trajectories differentiated by the primary (0 to 6 years of schooling at the time of the tsunami), secondary (7 to 12 years of schooling), and college (13 or more years of schooling) education cohorts. Among the college-educated cohort in both the heavy and other exposure groups, real hourly wages fell by 19.2%

and 18.7% respectively in the first year post-tsunami (Columns 7-9). These losses completely dissipated in subsequent years, and by the tenth year, wages for the college-educated cohort in both exposure groups had risen to 17.9% and 14.0% above their respective pre-tsunami levels. In comparison, while wages for the primary and secondary school cohorts in the other group also recovered and surpassed pre-tsunami levels, their peers in the heavy exposure group did not fare as well (Columns 1-6). Primary school educated workers in the heavy exposure group were especially devastated. They experienced a 48.3% wage decrease in the first year, which was 29.2 p.p. larger than the equivalent decline for their peers in the other group, and their wages remained more than 20% below baseline throughout the rest of the study period. All in all, it is clear that, particularly among the individuals most impacted by the tsunami, the highly educated were best able to recover in terms of their earnings. This positive relationship between education and post-disaster resiliency is consistent with prior research.

We next turn our attention to how post-tsunami labor supply adjustments differed across education cohorts (Table 8). Given that poorly educated workers experienced greater wage losses and were less likely to possess the savings or social capital necessary for income smoothing via non-labor means, one would expect the less educated cohorts to see greater increases to their work hours. However, the evidence tells a different story. Among the individuals living in heavily damaged communities at the time of the tsunami, the college-educated cohort spent 5.39 more hours working in the second year relative to before the tsunami (Column 7) while hours for the primary and secondary cohorts only peaked at 3.66 and 2.13 hours over their respective pre-tsunami levels (Columns 1 & 4). One explanation for this disparity is that the tsunami reduced demand for less educated workers, which restricted the ability of the primary and secondary school cohorts to smooth any income losses through work hours adjustments.

In the other exposure group, however, the primary and secondary school cohorts did experience greater hours increases than the college educated cohort. While college-educated males in the other group worked, at most, only 0.98 more hours over their pre-tsunami levels (Column 8), the primary and secondary cohorts peaked at 4.24 and 4.74 additional hours over baseline (Columns 2 & 5).

Labor Outcome Heterogeneity by Job Industry and Sector

In this subsection, I will discuss how the post-tsunami evolution of wages and hours-of-work differed by job industry and sector. Additionally, I will complement this analysis by documenting individual transitions across job types in the aftermath of the tsunami.

Industry

The evolution of post-tsunami wages for the agricultural, construction, and other off-farm industries are reported in Table 9. In both exposure groups, agricultural workers fared worse than those employed in other industries in terms of their earnings. Among workers in the heavy exposure group, agricultural wages fell by a precipitous 41.1% in the first year and remained 17.6% below pre-tsunami levels in the tenth year (Column 1), whereas their peers employed off-farm (excluding construction) experienced a 31.6% wage decline in the first year and recovered to within 2.4% of baseline wages by the end of the study period (Column 7). Likewise, agricultural wages for those in the other exposure group fell by 25.8% in the first year and peaked at 7.5% above baseline in the fifth year (Column 2) while wages for non-construction off-farm workers in the other group rose by 18.3% in the long run (Column 8). More strikingly, construction wages substantially outperformed other industries for workers in both exposure groups, especially in the short-term. After an initial 20.3% decline, construction wages for the heavy exposure group recovered to baseline by the next year and remained within 5% of pre-tsunami levels into the fifth year post-tsunami (Column 4). Construction wages in other areas even experienced significant growth in the short term, surging to 33.2% above baseline levels in the third year.

We also observe substantial heterogeneity in the hours-of-work adjustments by industry, particularly among workers in the heavy exposure group (Table 10). For males residing in heavily damaged areas at the time of the tsunami, only those employed in non-construction off-farm industries worked significantly longer hours following the disaster, while agricultural workers reduced their work hours throughout most of the post-tsunami period (Columns 1, 4 & 7). In contrast, all workers in the other exposure group increased their labor supply along the intensive margin, although hours for agricultural workers only peaked at 2.38 above baseline (Column 2) while those employed in construction or other off-farm industries worked over five more hours per week during the first two years post-tsunami (Columns 5 & 8).

Finally, Table 11 documents the individual post-tsunami transitions between industries[9]. We observe a substantial reallocation of labor away from the agricultural industry in the aftermath of the tsunami. In the first year, workers in heavily damaged and other areas were 19.0 p.p. and 13.4 p.p. less likely respectively to be employed in agriculture than at baseline (Columns 1-2). This shift persisted until the end of the study period, although some workers do return to agricultural employment. At the same time, workers in the heavy exposure group were 9.0 p.p. more likely to be in construction by the second year while workers in the other exposure group were also 6.3 p.p. more likely to be employed in construction in the fourth year (Columns 4-5).

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[9] Results for the "agriculture," "construction," and "other off-farm" column groups in Table 11 are obtained separately by estimating model [5] on industry indicators that take on the value of one for employment in certain industry and zero for employment elsewhere.

These changes reflect an effective doubling in the size of the construction industry since, before the tsunami, only 7.7% and 6.5% of all workers in the heavy and other groups were employed in construction.

All in all, the evidence presented here reflects a significant surge in post-tsunami construction labor demand. Across the entire sample, construction wages outperformed other industries, and construction labor supply grew as well, particularly along the extensive margin. This conclusion is consistent with prior literature in the context of other disasters as well as with the size and scale of the post-tsunami reconstruction effort, which were, by then, the largest in the developing world (Masyrafah & McKeon, 2008). Young and physically fit males were well-positioned to take advantage of the demand for construction-related labor, which potentially explains their strong recovery in terms of earnings.

These findings also show that the tsunami was devastating towards agricultural workers, especially those in the heavy exposure group. For the individuals residing in heavily damaged communities at the time of the tsunami, agricultural wages collapsed and never recovered while agricultural labor supply contracted as well along both the intensive and extensive margins. This likely had a disproportionate impact on less educated workers, which may explain why the primary and secondary education cohorts in the heavy exposure group both experienced large wage declines and were unable to mitigate this income loss through work hours adjustments.

Sector

Amongst market sector workers, wages declined by 28.3% and 21.7% in the first year for the heavy and other exposure groups respectively (Table 12, Columns 1 & 2). In subsequent years, market sector wages for both exposure groups eventually recovered, although the other group experienced greater long-term earnings growth. In comparison, there is a larger disparity in the post-tsunami trajectories of self-employed wages between exposure groups, with those in the heavy exposure group being particularly worse off. Their wages fell by 35.6% in the first year, which was 13.9 p.p. larger than the equivalent decline for their peers in other areas and also remained at least 15% below baseline levels throughout the remainder of the study period (Columns 4-6). The size and persistence of these wage losses suggest that, particularly among those living in heavily damaged communities at the time of the tsunami, the disaster was more disruptive to the livelihoods of self-employed workers. This likely reflects damage to capital and infrastructure, which reduced the profitability of family enterprises and limited their access to markets.

In terms of hours-of-work adjustments, self-employed workers significantly increased their work hours post-tsunami, with the self-employed in both exposure groups working nearly three additional hours per week throughout the first three years. (Table 13, Columns 4-6). In contrast, while market sector workers in the other exposure group also experienced substantial work hours increases, weekly hours for market sector workers in the heavy exposure group only peaked at 1.83 above their pre-tsunami levels (Column 1-3). This muted work hours response for market sector workers in the heavy exposure group may reflect labor demand constraints. Unlike self-employed workers who are free to set their work hours, those in the market sector would not have been able to work longer hours if their firms opted to reduce labor inputs.

Post-tsunami, there was also a substantial reallocation of labor away from self-employment (Table 14).[10] By the second year, workers in the heavy and other exposure groups

[10] Table 14 reports the results of model [5] estimated on an indicator taking on the value of 1 if the individual was in the market sector and 0 if they were self-employed. I do not report the results of model [5] estimated on a self-

were 17.5 p.p. and 20.0 p.p. more likely to be in the market sector than before the tsunami. The size of the self-employed sector did partially recover in subsequent years, but by the tenth year, workers in the heavy and other exposure groups were still 10.4 p.p. and 11.1 p.p. more likely to be in the market sector than at the pre-tsunami baseline. These patterns are consistent with the wage trajectories discussed previously. As the tsunami destroyed capital and reduced the profitability of family enterprises, those self-employed workers would likely have transitioned to market sector employment in search of higher earnings.

employment dummy as the resulting coefficients would be redundant. A 20.0 p.p. increase in the probability of market sector employment corresponds to a 20.0 p.p. decrease in self-employment.

7. Conclusion & Extensions for Future Work

Natural disasters can have devastating consequences towards the livelihoods of affected populations. This paper studies the effects of the 2004 Indian Ocean Tsunami on male labor market outcomes. Taking into account individual-specific heterogeneity through fixed effects models, I trace the causal impact of tsunami exposure on individual wages and labor supply throughout a period spanning ten years post-tsunami.

I find that wages declined substantially for all workers in the immediate aftermath of the tsunami, regardless of their individual exposure to the disaster. However, the wage losses of those residing in heavily damaged communities at the time of the tsunami persisted into the long run whereas their peers in other areas recovered and experienced substantial wage growth. Beyond these aggregate results, I explore the rich heterogeneity in post-tsunami wage trajectories and provide evidence, first, that younger and better educated workers had stronger recoveries in terms of labor outcomes, and second, that the livelihoods of agricultural and self-employed workers were particularly disrupted by the tsunami.

Additionally, I document the individual labor supply responses to this large and unanticipated shock. I find that work hours increased for all workers post-tsunami in spite of the major wage declines. This result is suggestive of income-smoothing behavior through labor market mechanisms. Many workers also reallocated their labor away from agriculture and self-employment towards the segments of the labor market that were less negatively affected by the tsunami.

When taken together, this paper makes several significant contributions to the literature on natural disasters and their effects on labor markets and well-being. First, I provide evidence that a massive and unanticipated natural disaster has long-term consequences for the livelihoods of impacted individuals. This contrasts with prior literature in the context of less destructive disasters and qualifies the existing macro-economic results on the long-term effects of the 2004 tsunami. Second, I show that individuals reacted to the tsunami by both increasing the number of hours they work, and by transitioning to better employment opportunities, and likely used these channels to mitigate the losses to their incomes and well-being. Finally, I build upon the existing literature on disaster resiliency by identifying older and less educated males as the subgroups the fared the worst post-tsunami in terms of their labor market outcomes.

To extend the results presented in this paper, several strands of future research appear promising. First, I restrict my analysis in this paper to only the tsunami's impact on male labor outcomes given the data limitations and self-selection for female labor participation. Nonetheless, the question of how natural disasters affect female experiences in the labor market is, in itself, an important area of study. Female labor participation did increase substantially post-tsunami, so there were likely other trends in female earnings and employment patterns that future research should investigate. However, any analysis of female labor outcomes will need to account for the self-selection into the labor market, which is endogenous to both the woman's own characteristics and those of the household.

Second, labor demand in heavily damaged areas may have collapsed post-tsunami due to destruction to capital and infrastructure. In this paper, I hypothesize that low labor demand restricted the ability of workers in the heavy exposure group, especially those in agriculture, the market sector, or with low levels of education, to make major adjustments to their work hours. Future work should evaluate these claims by directly examining tsunami impact on the demand side of labor markets.

Third, migration likely had a large effect on the observed labor market trajectories. The displacement of people from heavily damaged communities likely contributed to the spillover wage effect by increasing the labor supply in other areas. Further post-tsunami migrations may have also led to the long-term convergence in wage levels observed between exposure groups. Future research should explore the role of migration decisions in determining post-tsunami individual labor market outcomes. A potential starting point for this line of work could be in comparing the earnings or employment patterns between individuals who remained in heavily damaged areas and those who relocated elsewhere.

Ultimately, further research along these lines will help establish a clearer understanding of the true costs that natural disasters incur on individuals, communities, and economies. As disasters grow in frequency and severity, knowledge in this regard will only become ever more valuable.

Tables of Results

Table 3: Trajectories of Post-Tsunami Log Real Hourly Wages

	Heavy (1)	Other (2)	Difference (3)
Pre-tsunami	1.504	1.140	0.365***
			(0.071)
Changes post-tsunami			
Year 1	-0.321***	-0.218***	-0.103
	(0.0510)	(0.0277)	(0.0548)
Year 2	-0.141**	-0.0517	-0.0894
	(0.0511)	(0.0359)	(0.0585)
Year 3	-0.148**	0.0654	-0.214***
	(0.0521)	(0.0358)	(0.0588)
Year 4	-0.141*	0.0768*	-0.217***
	(0.0583)	(0.0323)	(0.0629)
Year 5	-0.0788	0.126***	-0.205**
	(0.0590)	(0.0322)	(0.0632)
Year 10	-0.0733	0.141***	-0.215**
	(0.0603)	(0.0353)	(0.0668)

\# of Individuals: 5,693
\# of Observations: 28,990
R-sq: 0.529
Dependent variable is individual log real hourly wages
Individual and month-of-interview fixed effects used
Clustered standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Trajectories of Post-Tsunami Hours Worked per Week

	Heavy (1)	Other (2)	Difference (3)
Pre-tsunami	45.953	42.003	3.950***
			(1.120)
Changes post-tsunami			
Year 1	1.540	4.307***	-2.767
	(1.457)	(0.743)	(1.495)
Year 2	2.412	4.239***	-1.827
	(1.382)	(0.775)	(1.405)
Year 3	2.970*	3.483***	-0.513
	(1.378)	(0.778)	(1.426)
Year 4	1.047	2.952***	-1.905
	(1.349)	(0.707)	(1.361)
Year 5	-0.138	2.652***	-2.790*
	(1.350)	(0.653)	(1.386)
Year 10	-0.539	2.770***	-3.309*
	(1.253)	(0.703)	(1.282)

\# of Individuals: 5,893
\# of Observations: 32,298
R-sq: 0.358
Dependent variable is individual weekly work hours
Individual and month-of-interview fixed effects used
Clustered standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Trajectories of Post-Tsunami Log Real Hourly Wages by Birth Cohort

	Young			Middle			Older		
	Heavy	Other	Difference	Heavy	Other	Difference	Heavy	Other	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pre-tsunami	1.266	0.956	0.310**	1.521	1.176	0.345***	1.620	1.213	0.407***
			(0.092)			(0.086)			(0.100)
Changes post-tsunami									
Year 1	-0.133	-0.200***	0.0667	-0.368***	-0.213***	-0.155	-0.384***	-0.231***	-0.152
	(0.0930)	(0.0365)	(0.0978)	(0.0739)	(0.0359)	(0.0787)	(0.0814)	(0.0353)	(0.0876)
Year 2	0.0624	0.0117	0.0507	-0.179*	-0.0510	-0.128	-0.222**	-0.0902*	-0.132
	(0.0956)	(0.0519)	(0.107)	(0.0768)	(0.0458)	(0.0861)	(0.0781)	(0.0450)	(0.0873)
Year 3	0.0242	0.141**	-0.117	-0.163*	0.0588	-0.222**	-0.234*	0.0229	-0.257*
	(0.0997)	(0.0514)	(0.111)	(0.0714)	(0.0474)	(0.0820)	(0.102)	(0.0457)	(0.108)
Year 4	-0.0245	0.178***	-0.203	-0.0917	0.0730	-0.165	-0.250**	0.0101	-0.260**
	(0.0957)	(0.0469)	(0.104)	(0.0871)	(0.0434)	(0.0943)	(0.0920)	(0.0424)	(0.0988)
Year 5	0.114	0.200***	-0.0860	-0.0816	0.155***	-0.237*	-0.197	0.0557	-0.253*
	(0.0795)	(0.0484)	(0.0895)	(0.0865)	(0.0424)	(0.0940)	(0.104)	(0.0426)	(0.110)
Year 10	0.138	0.267***	-0.129	-0.0463	0.169***	-0.215*	-0.286**	-0.00525	-0.281*
	(0.0823)	(0.0488)	(0.0932)	(0.0821)	(0.0471)	(0.0923)	(0.110)	(0.0501)	(0.119)

\# of Individuals: 5,693
\# of Observations: 28,990
R-sq: 0.530
Dependent variable is individual log real hourly wages
Individual and month-of-interview fixed effects used
Clustered standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Trajectories of Post-Tsunami Weekly Work Hours by Birth Cohort

	Young			Middle			Older		
	Heavy	Other	Difference	Heavy	Other	Difference	Heavy	Other	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pre-tsunami	45.431	41.720	3.711*	46.910	42.344	4.566*	45.313	41.928	3.385
			(1.312)			(1.442)			(1.250)
Changes post-tsunami									
Year 1	2.649	5.038***	-2.389	1.202	4.732***	-3.529	1.100	3.394***	-2.293
	(2.121)	(0.960)	(2.214)	(1.860)	(0.930)	(1.983)	(1.983)	(0.848)	(2.051)
Year 2	2.050	5.418***	-3.369	2.554	4.506***	-1.952	2.766	3.137***	-0.370
	(1.796)	(1.080)	(1.920)	(1.737)	(0.854)	(1.813)	(1.826)	(0.891)	(1.911)
Year 3	4.528*	4.686***	-0.159	2.390	3.771***	-1.382	2.342	2.315*	0.0274
	(1.917)	(1.077)	(2.070)	(1.769)	(0.908)	(1.879)	(1.700)	(0.924)	(1.811)
Year 4	2.599	4.393***	-1.794	1.067	3.260***	-2.193	-0.234	1.582	-1.816
	(1.852)	(0.939)	(1.931)	(1.635)	(0.871)	(1.748)	(1.711)	(0.806)	(1.766)
Year 5	1.056	4.131***	-3.076	-0.00203	3.445***	-3.447	-1.177	0.831	-2.008
	(1.829)	(0.881)	(1.936)	(1.792)	(0.821)	(1.893)	(1.552)	(0.787)	(1.637)
Year 10	2.125	4.820***	-2.696	-1.229	3.008***	-4.237*	-2.501	0.675	-3.176
	(1.552)	(0.877)	(1.644)	(1.664)	(0.866)	(1.763)	(1.569)	(0.880)	(1.687)

\# of Individuals: 5,893
\# of Observations: 32,298
R-sq: 0.359
Dependent variable is individual weekly work hours
Individual and month-of-interview fixed effects used
Clustered standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Trajectories of Post-Tsunami Log Real Hourly Wages by Education Cohort

	Primary			Secondary			College		
	Heavy	Other	Difference	Heavy	Other	Difference	Heavy	Other	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pre-tsunami	1.395	0.877	0.518***	1.439	1.244	0.195*	2.117	2.138	-0.021
			(0.109)			(0.076)			(0.113)
Changes post-tsunami									
Year 1	-0.483***	-0.191***	-0.292**	-0.255***	-0.241***	-0.0143	-0.192	-0.187**	-0.00529
	(0.0972)	(0.0385)	(0.103)	(0.0576)	(0.0310)	(0.0623)	(0.105)	(0.0601)	(0.119)
Year 2	-0.213*	-0.0248	-0.188	-0.0907	-0.0776	-0.0131	-0.130	0.0144	-0.145
	(0.0989)	(0.0507)	(0.110)	(0.0622)	(0.0404)	(0.0707)	(0.0912)	(0.0760)	(0.115)
Year 3	-0.266**	0.0692	-0.335**	-0.102	0.0546	-0.156*	-0.0226	0.152	-0.174
	(0.0973)	(0.0508)	(0.108)	(0.0647)	(0.0424)	(0.0739)	(0.103)	(0.0836)	(0.130)
Year 4	-0.288**	0.0732	-0.362**	-0.0590	0.0805*	-0.140	-0.0824	0.0854	-0.168
	(0.105)	(0.0424)	(0.111)	(0.0714)	(0.0392)	(0.0786)	(0.111)	(0.0744)	(0.131)
Year 5	-0.294*	0.148***	-0.442***	0.00824	0.110**	-0.101	0.0962	0.151	-0.0549
	(0.118)	(0.0421)	(0.123)	(0.0650)	(0.0391)	(0.0724)	(0.0905)	(0.0931)	(0.127)
Year 10	-0.257*	0.148**	-0.405**	-0.0299	0.138***	-0.168*	0.179	0.140	0.0384
	(0.113)	(0.0529)	(0.124)	(0.0669)	(0.0403)	(0.0759)	(0.106)	(0.0955)	(0.141)

\# of Individuals: 5,693
\# of Observations: 28,990
R-sq: 0.530
Dependent variable is individual log real hourly wages
Individual and month-of-interview fixed effects used
Clustered standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Trajectories of Post-Tsunami Weekly Work Hours by Education Cohort

	Primary			Secondary			College		
	Heavy	Other	Difference	Heavy	Other	Difference	Heavy	Other	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pre-tsunami	45.043	40.644	4.399*	47.730	43.259	4.471***	39.092	40.361	-1.269
			(1.922)			(1.255)			(1.490)
Changes post-tsunami									
Year 1	2.152	4.242***	-2.090	1.211	4.642***	-3.431	1.733	0.982	0.751
	(2.372)	(0.864)	(2.413)	(1.669)	(0.890)	(1.783)	(2.243)	(1.328)	(2.551)
Year 2	3.660	4.011***	-0.351	1.046	4.736***	-3.690*	5.390**	0.432	4.958*
	(2.390)	(0.866)	(2.423)	(1.604)	(0.906)	(1.697)	(1.689)	(1.363)	(2.098)
Year 3	3.656	3.881***	-0.225	2.127	3.451***	-1.324	5.135*	-0.0179	5.153*
	(2.316)	(0.910)	(2.383)	(1.540)	(0.923)	(1.661)	(2.161)	(1.374)	(2.488)
Year 4	1.533	3.356***	-1.823	0.0155	2.925***	-2.909	4.481*	-0.478	4.959*
	(2.340)	(0.849)	(2.378)	(1.503)	(0.834)	(1.590)	(2.022)	(1.201)	(2.271)
Year 5	0.918	3.098***	-2.180	-1.102	2.446**	-3.548*	1.839	0.608	1.231
	(2.319)	(0.763)	(2.359)	(1.458)	(0.800)	(1.577)	(1.955)	(1.276)	(2.282)
Year 10	-0.0851	2.610**	-2.695	-1.724	3.016***	-4.740**	3.560*	0.620	2.940
	(2.265)	(0.860)	(2.302)	(1.423)	(0.804)	(1.528)	(1.562)	(1.261)	(1.947)

\# of Individuals: 5,893
\# of Observations: 32,298
R-sq: 0.359
Dependent variable is individual weekly work hours
Individual and month-of-interview fixed effects used
Clustered standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Trajectories of Post-Tsunami Log Real Hourly Wages by Industry

	Agriculture			Construction			Other Off-farm Industries		
	Heavy	Other	Difference	Heavy	Other	Difference	Heavy	Other	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pre-tsunami	1.267	0.902	0.365**	1.417	1.101	0.317	1.703	1.491	0.212
			(0.112)			(0.193)			(0.076)
Changes post-tsunami									
Year 1	-0.411***	-0.258***	-0.153	-0.203*	-0.0773	-0.126	-0.316***	-0.208***	-0.108
	(0.112)	(0.0375)	(0.117)	(0.0837)	(0.0508)	(0.0953)	(0.0554)	(0.0290)	(0.0593)
Year 2	-0.315***	-0.102*	-0.213*	0.0734	0.162*	-0.0887	-0.133*	-0.0545	-0.0790
	(0.0874)	(0.0458)	(0.0945)	(0.102)	(0.0629)	(0.117)	(0.0563)	(0.0381)	(0.0648)
Year 3	-0.246**	-0.0183	-0.228*	-0.0452	0.332***	-0.377***	-0.134*	0.0828*	-0.217**
	(0.0910)	(0.0465)	(0.0980)	(0.0741)	(0.0609)	(0.0923)	(0.0586)	(0.0379)	(0.0663)
Year 4	-0.144	0.0254	-0.169	-0.0284	0.220***	-0.248*	-0.163*	0.0876*	-0.251***
	(0.0934)	(0.0388)	(0.0975)	(0.0968)	(0.0516)	(0.109)	(0.0634)	(0.0387)	(0.0711)
Year 5	-0.226*	0.0746	-0.301**	0.0820	0.299***	-0.217*	-0.0451	0.130***	-0.175*
	(0.0961)	(0.0402)	(0.101)	(0.0893)	(0.0484)	(0.0990)	(0.0607)	(0.0382)	(0.0683)
Year 10	-0.176	0.0704	-0.246*	-0.0970	0.231***	-0.328**	-0.0244	0.183***	-0.207**
	(0.107)	(0.0497)	(0.116)	(0.114)	(0.0519)	(0.123)	(0.0630)	(0.0378)	(0.0707)

\# of Individuals: 5,693
\# of Observations: 28,990
R-sq: 0.532
Dependent variable is individual log real hourly wages
Individual and month-of-interview fixed effects used
Clustered standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Trajectories of Post-Tsunami Weekly Work Hours by Industry

	Agriculture			Construction			Other Off-farm Industries		
	Heavy	Other	Difference	Heavy	Other	Difference	Heavy	Other	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pre-tsunami	43.910	39.385	4.525**	49.198	46.338	2.860	47.175	45.277	1.898
			(1.717)			(1.921)			(1.314)
Changes post-tsunami									
Year 1	-1.792	2.358**	-4.150*	-0.0336	5.967***	-6.001*	3.116*	5.805***	-2.689
	(1.970)	(0.910)	(2.066)	(2.323)	(1.176)	(2.516)	(1.530)	(0.800)	(1.588)
Year 2	-0.0943	2.236*	-2.330	1.511	5.049***	-3.538	3.652*	5.856***	-2.205
	(1.630)	(0.864)	(1.703)	(1.678)	(1.086)	(1.868)	(1.531)	(0.878)	(1.610)
Year 3	1.412	2.375**	-0.963	2.215	3.338**	-1.122	3.726*	4.468***	-0.742
	(1.795)	(0.888)	(1.860)	(1.940)	(1.138)	(2.168)	(1.507)	(0.865)	(1.595)
Year 4	-1.176	1.548	-2.724	-1.623	3.271***	-4.894**	2.758	4.225***	-1.468
	(1.826)	(0.807)	(1.848)	(1.740)	(0.865)	(1.853)	(1.472)	(0.828)	(1.548)
Year 5	-0.992	1.535*	-2.527	-2.551	3.111***	-5.662**	0.876	3.811***	-2.936
	(1.703)	(0.736)	(1.774)	(1.908)	(0.884)	(2.016)	(1.414)	(0.766)	(1.496)
Year 10	-1.549	1.472	-3.021	-0.996	3.207**	-4.204*	0.132	4.030***	-3.898**
	(1.568)	(0.792)	(1.623)	(1.539)	(1.066)	(1.765)	(1.328)	(0.801)	(1.410)

\# of Individuals: 5,893
\# of Observations: 32,298
R-sq: 0.361
Dependent variable is individual weekly work hours
Individual and month-of-interview fixed effects used
Clustered standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Trajectories of the Post-Tsunami Proportion of Workers in Each Industry

	Agriculture			Construction			Other Off-farm Industries		
	Heavy	Other	Difference	Heavy	Other	Difference	Heavy	Other	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pre-tsunami	0.423	0.571	-0.148**	0.077	0.065	0.013	0.500	0.365	0.135**
			(0.045)			(0.014)			(0.040)
Changes post-tsunami									
Year 1	-0.190***	-0.134***	-0.0563	0.0753***	0.0276**	0.0477*	0.115***	0.106***	0.00859
	(0.0318)	(0.0160)	(0.0343)	(0.0209)	(0.00962)	(0.0221)	(0.0313)	(0.0154)	(0.0337)
Year 2	-0.183***	-0.145***	-0.0379	0.0901***	0.0470***	0.0431*	0.0926**	0.0977***	-0.00515
	(0.0292)	(0.0160)	(0.0318)	(0.0198)	(0.0101)	(0.0202)	(0.0287)	(0.0155)	(0.0302)
Year 3	-0.179***	-0.146***	-0.0336	0.0686***	0.0473***	0.0212	0.111***	0.0985***	0.0123
	(0.0304)	(0.0162)	(0.0330)	(0.0192)	(0.0105)	(0.0199)	(0.0306)	(0.0161)	(0.0327)
Year 4	-0.126***	-0.137***	0.0110	0.0562**	0.0627***	-0.00655	0.0697*	0.0741***	-0.00440
	(0.0274)	(0.0153)	(0.0301)	(0.0177)	(0.0101)	(0.0181)	(0.0282)	(0.0148)	(0.0298)
Year 5	-0.128***	-0.114***	-0.0134	0.0598***	0.0598***	0.0000562	0.0677**	0.0544***	0.0134
	(0.0242)	(0.0142)	(0.0270)	(0.0163)	(0.00966)	(0.0176)	(0.0254)	(0.0134)	(0.0273)
Year 10	-0.0931***	-0.112***	0.0187	0.0288	0.0431***	-0.0143	0.0643**	0.0688***	-0.00441
	(0.0233)	(0.0151)	(0.0260)	(0.0157)	(0.00939)	(0.0162)	(0.0237)	(0.0144)	(0.0259)

\# of Individuals: 5,897

\# of Observations: 32,438

R-sq: 0.636

Dependent variables are indicators equalling 1 if individual is employed in a particular industry and 0 for employment elsewhere

Individual and month-of-interview fixed effects used

Clustered standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Trajectories of Post-Tsunami Log Real Hourly Wages by Sector

	Market Sector			Self-Employed		
	Heavy	Other	Difference	Heavy	Other	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-tsunami	1.688	1.432	0.257**	1.405	0.990	0.415***
			(0.082)			(0.086)
Changes post-tsunami						
Year 1	-0.283***	-0.217***	-0.0667	-0.356***	-0.217***	-0.139*
	(0.0567)	(0.0316)	(0.0623)	(0.0669)	(0.0312)	(0.0710)
Year 2	-0.0937	-0.0205	-0.0732	-0.192**	-0.0887*	-0.103
	(0.0577)	(0.0386)	(0.0656)	(0.0676)	(0.0420)	(0.0768)
Year 3	-0.108	0.0701	-0.178**	-0.193**	0.0599	-0.253**
	(0.0583)	(0.0383)	(0.0655)	(0.0671)	(0.0433)	(0.0765)
Year 4	-0.132*	0.0885**	-0.220**	-0.151*	0.0659	-0.217**
	(0.0661)	(0.0338)	(0.0708)	(0.0742)	(0.0386)	(0.0806)
Year 5	0.00853	0.154***	-0.145*	-0.158*	0.103**	-0.261***
	(0.0586)	(0.0329)	(0.0639)	(0.0715)	(0.0389)	(0.0780)
Year 10	0.0618	0.206***	-0.144*	-0.214**	0.0727	-0.287**
	(0.0568)	(0.0352)	(0.0636)	(0.0782)	(0.0455)	(0.0885)

\# of Individuals: 5,693

\# of Observations: 28,990

R-sq: 0.530

Dependent variable is individual log real hourly wages

Individual and month-of-interview fixed effects used

Clustered standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Trajectories of Post-Tsunami Weekly Work Hours by Sector

	Market Sector			Self-Employed		
	Heavy	Other	Difference	Heavy	Other	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-tsunami	44.939	43.874	1.065	46.472	41.044	5.428***
			(1.473)			(1.284)
Changes post-tsunami						
Year 1	0.0873	4.884***	-4.796**	2.999	3.826***	-0.827
	(1.533)	(0.848)	(1.622)	(1.682)	(0.805)	(1.743)
Year 2	1.695	4.408***	-2.713	3.173	4.030***	-0.857
	(1.362)	(0.833)	(1.411)	(1.627)	(0.862)	(1.701)
Year 3	1.832	4.105***	-2.273	4.097**	2.841***	1.255
	(1.438)	(0.840)	(1.536)	(1.581)	(0.845)	(1.642)
Year 4	-0.613	3.027***	-3.640*	2.682	2.853***	-0.171
	(1.539)	(0.742)	(1.562)	(1.434)	(0.775)	(1.484)
Year 5	-1.837	2.881***	-4.718**	1.310	2.424***	-1.115
	(1.470)	(0.717)	(1.527)	(1.414)	(0.722)	(1.485)
Year 10	0.0333	3.117***	-3.084*	-1.197	2.448**	-3.645*
	(1.287)	(0.708)	(1.326)	(1.401)	(0.821)	(1.484)

# of Individuals: 5,893
# of Observations: 32,298
R-sq: 0.359
Dependent variable is individual weekly work hours
Individual and month-of-interview fixed effects used
Clustered standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Trajectories of the Post-Tsunami Proportion of Workers in the Market Sector

	Market Sector		
	Heavy	Other	Difference
	(1)	(2)	(3)
Pre-tsunami	0.339	0.338	0.001
			(0.036)
Changes post-tsunami			
Year 1	0.150***	0.0996***	0.0505
	(0.0337)	(0.0198)	(0.0365)
Year 2	0.175***	0.200***	-0.0249
	(0.0326)	(0.0198)	(0.0350)
Year 3	0.174***	0.177***	-0.00348
	(0.0271)	(0.0213)	(0.0299)
Year 4	0.173***	0.140***	0.0330
	(0.0302)	(0.0194)	(0.0324)
Year 5	0.119***	0.124***	-0.00521
	(0.0312)	(0.0184)	(0.0335)
Year 10	0.104***	0.111***	-0.00636
	(0.0261)	(0.0187)	(0.0291)

# of Individuals: 5,897
# of Observations: 32,438
R-sq: 0.503
Dependent variable is an indicator equalling one if individual is employed in the market sector and zero for self-employment
Individual and month-of-interview fixed effects used
Clustered standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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