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Natural Disasters and Labour Markets

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ABSTRACT

While it is clear that natural disasters have serious welfare consequences for affected populations, less is known with respect to how local labour markets in low income countries adjust to such large shocks, in particular the general equilibrium effects of the increase in the demand for construction as well as the inflow of resources in the aftermath of natural disasters. Combining data from the Indonesia Family Life Survey, the Desinventar database, the US Geological Survey and district level employment indicators, this paper explores how a large earthquake in Indonesia affected local labour markets, in particular the evolution of wages and employment across sectors. We find that wage growth in the agriculture sector is significantly higher in earthquake affected areas. We propose two mechanisms for this result: a higher growth rate of the price of rice in agricultural communities which switch from being net sellers to net buyers of rice and a downward shift in the supply of workers in the agricultural sector. We show evidence for both mechanisms.

Keywords: Local labour markets, natural disasters.

JEL Classification: J20, Q54, O10.

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1 Introduction

The objective of this paper is to understand the effects of large scale destructive shocks on labour markets in lower and middle income countries. Such shocks have two distinct features: first, a large proportion of the damage occurs in the housing sector; for example, 40% of the damage and losses from the 2010 earthquake in Haiti were due to destroyed and damaged housing (Government of Haiti et al 2010) and this share is even higher for other earthquakes (BNPB et al 2009; BAPPENAS 2006). Second, once the emergency phase is over, aid flows earmarked for reconstruction often last for several years following the disaster. Fund allocations following the 2004 tsunami to the housing sector in Aceh in Indonesia amounted to $US 1.6 billion, which is equivalent to 25% of total reconstruction funding and 30% of Aceh's regional GDP, and were rising for several years after the tsunami. There is increasing micro level evidence on the effect of natural disasters on poverty, expenditures, incomes, remittances and child health from developing countries (Anttila-Hughes and Hsiang 2013; Baez and Santos 2008; Halliday 2006; Premand 2008; Yang 2008). Little is known about how labour markets are affected by the interaction of the initial human and physical destruction and the inflow of resources in the aftermath which are largely spent in non-tradable sectors of the local economy[1]. This paper aims to contribute toward filling this gap.

We use a large earthquake hitting Yogyakarta in Indonesia on 27 May 2006 at 05:53:58 am to study the labour market effects of large destructive shocks. The Yogyakarta earthquake was one of the costliest disasters in the past 10 years and disaster response was coordinated and swift. It is therefore a useful example to study the combined effect of the destruction and large inflows of resources. To measure the effect of the earthquake, we use data on houses destroyed as well as an exogenous measure that is based on recorded ground motions. We link these with data from the Indonesia Family Life Survey, which contains detailed labour market information and is the only large scale individual level panel survey in Indonesia. Since sectoral choice of individuals is likely to be correlated with time invariant and time varying unobservables, it is vital to have information on the sector of employment before the earthquake took place. To unpack the mechanisms and measure general equilibrium effects, we use community level price data and district level employment indicators from the Socio-Economic Surveys in 2004 and 2007.

The central contribution of this paper is to understand how resilient labour markets are when hit by a large scale shock and how the effects of the shock work through labour markets in the context of a lower middle income country with a high level of informality. Compared to natural disasters in high income countries, we would expect the post-disaster state in low income countries to be different along at least two dimensions: first, instantaneous capital liquidity might be a constraint delaying disbursement of funds and thereby the response in the immediate aftermath of a disaster (World Bank 2012a); second, social safety nets are incomplete and there is a high level of informality of the labour market meaning that livelihood reconstruction is an utmost priority. As opposed to the response to the deaths and devastation caused by the December 2004 Tsunami in Aceh in Indonesia, the response to the 2006 Yogyakarta earthquake has in general been regarded as

[1] Exceptions using county level data for the United States are Belasen and Polachek (2008), Belasen and Polachek (2009) and Deryugina (2013).

a swift and efficient response. It is therefore instructive as a case study of a coordinated post-disaster response in a highly informal labour market.

Understanding the labour market effects of natural disasters is important as the damage from natural disasters has been rising in the past two decades (United Nations and World Bank 2010) with consequences in terms of deaths being concentrated in low-income countries (Kahn 2005). Labour markets are regarded to be playing a vital role in determining individual's and household's welfare. For example, the entire World Development Report 2013 is devoted to jobs and argues that "jobs are instrumental to achieving economic and social development. Beyond their critical importance for individual well-being, they lie at the heart of many broader societal objectives, such as poverty reduction, economy-wide productivity growth and social cohesion" (World Bank 2013). In order to optimally design responses to large disasters, it is crucial to understand the labour market consequences of such shocks[2]. Further, Anttila-Hughes and Hsiang (2013) highlight that considering the link between natural disasters and climate change, understanding the costs of natural disasters is important for the formulation of climate policy.

We find that labour markets are remarkably resilient against such large shocks and on average wage growth was even higher in earthquake affected regions. We do not find robust evidence for differences in the effect of the earthquake according to whether individuals are self-employed, firm owners, government workers or employed in the private sector. Given that these employment categories have different levels of job protection and regulations, this result is rather surprising. However, we do find substantial heterogeneity with respect to the sectoral evolution of wages. Individuals working in the agricultural sector in areas that were strongly affected by the earthquake enjoyed a substantially higher earnings growth compared to individuals working in the commercial services sector; individuals working in the commercial services sector did not have negative earnings growth effects. This suggests that local labour markets are fairly segmented and mobility is limited. In the agriculture sector this is likely to be the case since land as a factor of production is immobile, many farms are family farms, and monitoring of labour is fairly difficult in this sector. The result is robust to a range of specifications relying on alternative identifying assumptions compared to our preferred specification, including a differences-in-differences specification, fixed effects, a dynamic specification and a dynamic instrumental variables specification. A range of measures of the intensity of the earthquake shock and varying control groups also produce very consistent results.

We propose two mechanisms for this result. First, the destruction of infrastructure led to increases in the price of food, particularly in areas which are net consumers of food. Second, an increase in the demand for labour in sectors producing non-tradables in the aftermath of the disaster drew workers out of the agricultural sector (the low-wage sector) into higher-wage non-tradable

[2]While studying the effects of earthquakes on labour markets is important by itself, the earthquake shock can also be viewed as a rare occasion to study the structural transformation of local economies. Alvarez-Cuadrado and Poschke (2011) examine the importance of 'push factors' due to increased agricultural productivity and 'pull factors' due to increased technological progress in manufacturing in driving the structural transformation of 12 industrialised countries. The sharp exogenous rise in inflows of resources and demand for reconstruction allows isolating the increase in demand for labour outside the agricultural sector from increases in agricultural productivity and analyze their effects in a general equilibrium context.

sectors, leading to a rise in the marginal product of labour and wages in the agriculture sector. We find evidence for both mechanisms. The earthquake led to higher growth in the price of rice. We also show that the growth in rice prices was higher in communities which switched from being net producers to being net consumers. Employment in the agricultural sector contracted and expanded in the construction sector in the aftermath of the earthquake. The evidence suggests that both these effects resulted in higher wage growth for agricultural workers.

The paper contributes to an emerging literature on the effects of natural disasters on various outcomes, such as consumption, income, and migration. Studies of two earthquakes that struck El Salvador in 2001 find that the earthquake shock led to lower migration and a reduction in household income (Baez and Santos 2008; Halliday 2006; Yang 2008). Premand (2008) finds moderate short term effects of hurricane Mitch on consumption growth but no evidence for persistence. In contrast to these papers, we focus on labour markets, in particular heterogeneity across sectors and levels of formality[3]. The research most closely linked to this paper is by Belasen and Polachek (2008) and Belasen and Polachek (2009) who investigate the labour market consequences of hurricanes in Florida, exploiting differences in county-level earnings and employment rates calculated from quarterly data[4]. This paper differs from their study in that we use panel data of individuals, and investigate the effects of an exogenous shock in the context of a lower middle income country.

This paper also relates to a substantial body of literature in development economics exploring how shocks impact households along a number of dimensions, including households' ability to smooth consumption, ex-ante and ex-post coping strategies as well as short and long-term effects of shocks on a range of outcomes such as consumption, schooling, health and child work (Dercon 2004; Paxson 1992; Townsend 1994; Udry 1995)[5]. Jayachandran (2006) finds that agricultural productivity shocks have stronger negative effects on wages when workers are poorer, less mobile and more credit constrained. Mueller and Quisumbing (2010) find long term negative effects of floods on agricultural wages in Bangladesh. This paper focuses on the labour market consequences of a non-weather related large exogenous shock in a developing country.

A growing number of macroeconomic studies contribute to the ongoing debate in macroeconomics on whether natural disasters harm economic growth, foster it, have impacts only under certain conditions, or no impact at all (Cavallo et al. 2013; Fomby et al. 2011; Hochrainer 2009; Hsiang 2010; Loayza et al. 2012; Noy 2009; Strobl 2011)[6]. Studying the labour market in a micro

[3]On the firm side, De Mel et al. (2012) study the effects of cash grants on the recovery of Sri Lankan entreprises after the tsunami and find significant effects of grants on retailers, but little effect on firms in the manufacturing or services sector. Their main interest is in studying profits and the capital stock of firms.

[4]Some studies use hurricanes as natural experiments to investigate the impact of migration on receiving labour markets, for example see McIntosh (2008) and Silva et al. (2010).

[5]Employment in the non-agricultural sector has been found to be an important strategy for agricultural households to diversify their portfolio ex-ante as well as ex-post (Kochar 1999; Rose 2001).

[6]For a recent survey see Kellenberg and Mobarak (2011). The above cited papers (apart from Strobl (2011)) use data on natural disasters from the Emergency Disasters Database (EM-DAT), maintained by the Centre for Research on the Epidemiology of Disasters (CRED), and estimate cross country panel models to understand macroeconomic effects of natural disasters. Strobl (2011) computes a proxy of local destruction to estimate the effects of hurricanes on economic growth. Hsiang (2010) combines UN National Accounts data with data on various spatial data such as wind speed and temperature and shows a significant effect of temperature and cyclones on economic production in the Caribbean and

setting as done in this paper is a step towards providing evidence on the underlying mechanisms at play. Finally, the paper relates to research on the multiplier effect of job creation in the tradable sector (Moretti 2010b), on Dutch-disease (Corden and Neary 1982), the employment effects of construction projects (Carrington 1996), and labour market effects of oil price changes (Keane and Prasad 1996; Kline 2008).

Our findings imply that large-scale destruction coupled with a substantial inflow of financial resources has not significantly negatively affected wage growth. On the contrary, agricultural workers which had the lowest wages experienced faster wage growth, so that the earthquake led to faster convergence of wages across sectors. The finding that economies recover quickly from temporary shocks is in line with what Davis and Weinstein (2002) and Miguel and Roland (2011) find for bombings in Japan and Vietnam. Two limitations of the paper due to data constraints are that we are not able to separately identify the effects of destruction and reconstruction and that we can only look at short run effects (about 2 years after the shock). Both issues are important to establish a fuller picture of the welfare effects and thus important topics for future research.

The paper is structured as follows. Section 2 describes the Indonesian context and the data; section 3 provides a conceptual framework to outline the channels through which natural disasters might impact on local labour markets; section 4 discusses identification and estimation; section 5 presents the results and explores mechanisms. Section 6 concludes.

2 Context and Data

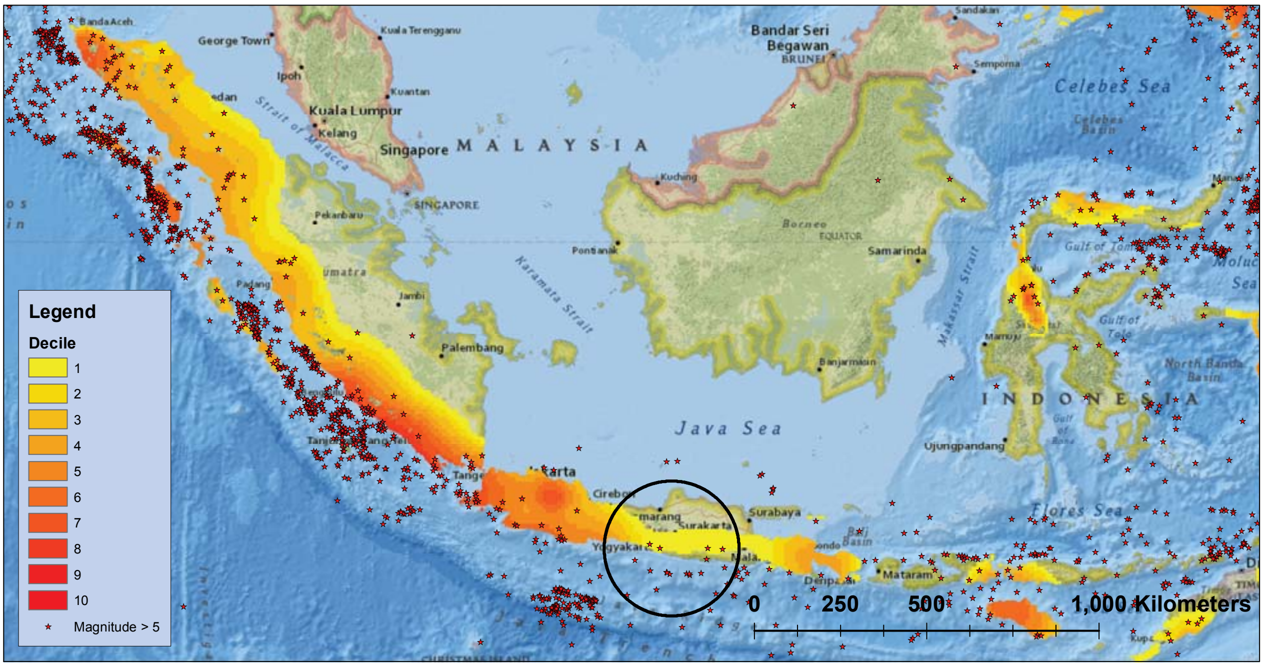
To investigate the effects of natural disasters on local labour markets, we study the effect of a large earthquake that hit Yogyakarta in Indonesia. Indonesia is one of the seismologically most active regions worldwide ranked third out of 153 countries in terms of absolute mortality risk from earthquakes (United Nations Office for Disaster Risk Reduction 2009). Since 2004, four seismic events alone affected 6.7 million people[7]. Figure 1 shows earthquakes with a magnitude larger than 5 on the Richter scale in the region between 2000-2008 and the percentiles of peak ground acceleration values for areas that exhibit a 10% chance of exceeding a peak ground acceleration of 2 metres per second in a 50 year period produced by the Center for Hazards and Risk Research and Center for International Earth Science Information Network (2005)[8]. Values of 2 metres per second and less were excluded. It is apparent from the map that Indonesia is exposed to a large number of earthquakes. Figure 1 also illustrates that despite differences in the predicted intensity of earthquakes, a large area in Indonesia is subject to substantial risk of future earthquakes. The impossibility to

Central America.

[7]The four events are: the 2004 Tsunami caused by an earthquake, the 2006 Yogyakarta earthquake, the 2009 Southern Sumatra earthquake, and the 2007 Southern Sumatra Tsunami (EM-DAT: The OFDA/CRED International Disaster Database 2014). The high level of seismic events is due to Indonesia's location on the boundary between the Sunda plate in the North-East and the Australia plate in the South-West. The Australia Plate is moving 50-60 mm per year northward with respect to the Sunda plate in the South-East and 40-50 mm per year northward in the North-West (US Geological Survey 2008). Inter-plate earthquakes (caused by the subduction of the Australia plate beneath the Sunda plate) and intra-plate earthquakes (caused by stresses generated in the subduction process) occur frequently.

[8]When an earthquake happens the ground shakes, but also accelerates. Peak ground acceleration is the largest increase in velocity recorded on the ground.

Figure 1: Earthquakes during 2000-2008, and Earthquake Hazard



Notes: Figure is produced using ArcGIS 10; earthquakes with a magnitude larger than 5 on the Richter scale from the United States Geological Survey and earthquake hazard from Center for Hazards and Risk Research and Center for International Earth Science Information Network (2005); Center for International Earth Science Information Network (CIESIN), Columbia University; International Bank for Reconstruction and Development/The World Bank.

predict earthquakes and thus exogeneity of the earthquake is crucial for our identification strategy.

The Yogyakarta earthquake took place on 27 May 2006 at 05:53:58 am with a magnitude of 6.3 and a shallow depth of 10 metres below sea level (US Geological Survey 2012). It was among the most costly natural disasters in developing countries in the past 10 years leading to damage and losses of about US$ 3.1 billion (International Recovery Platfrom 2009). More than 5700 people were killed, and about 280,000 houses were destroyed Java Reconstruction Fund (2007). However, the Indonesian governments' response was swift[9] and coordinated and pooled donor funding was channelled through the Java Construction Fund[10]. By June 2007, about 80% of the affected houses had been repaired or replaced (World Bank 2012b). Total recovery and reconstruction spending accounted for about 30% of the total damage of the earthquake[11].

We combine data from several sources. First, we use household level data from the Indonesia Family Life survey, a large-scale panel household survey conducted in 1993, 1997, 2000 and 2007. Being the only large-scale individual level longitudinal survey available in Indonesia, it is suitable

[9]The fast execution of funds can be partially attributed to the timing of the earthquake which as just in time for mid-year budget revision. Consequently, US$270 were spent by the end of October 2006.

[10]As of June 30, 11, seven donors (the European Union, the Netherlands, the United Kingdom, the Asian Development Bank, and the governments of Canada, Finland and Denmark) have contributed a total of US$91 million to the JRF. The main projects were a Housing and Community Recovery Project (absorbing 82% of the funds) and a Recovery of Livelihood Project absorbing the remaining 18% of the funds.

[11]The government of Indonesia disbursed US$610 million in the fiscal years 2006-2007; provincial and local governments contributed US$140 million, and contributions from donors were estimated at US$107 million (World Bank 2012a).

to study the dynamic behaviour of individuals. The initial sample includes 321 communities and is representative of 83% of the Indonesian population living in 13 of the country's 26 provinces[12]. With a re-contact rate in 2007 of 93.6% of the original IFLS 1 (1993) households it follows panel members equally well or better than surveys in developed countries (Strauss et al. 2009)[13]. In this study we use data for individuals aged 20-55 in 2000 living in the following provinces: Central Java, Yogyakarta, East Java and West Java. This leaves us with a sample of 2,471 individuals in treatment and control districts as defined below for whom we have complete information for 2000 and 2007[14]. Round 3 was conducted between July-December 2000 and round 4 took place between October 2007-July 2008.

The wage reported for a respondent's primary job forms the basis for computing wages. Wages for privately employed individuals are measured as last month's salary including the value of all benefits. For self-employed individuals, wages are computed using last month's net profits[15]. Following Strauss et al. (2004), we also compute hourly wages on the basis of monthly reported earnings divided by the total hours worked last week multiplied by 4.33[16]. All wages are expressed in 2007 Indonesian Rupiah[17].

Over the past 20 years, the Indonesian labour market has gone through a number of phases. The 1990s, and before the Asian crisis, in 1997, have been marked by rising employment and wages and a shift of the workforce out of agriculture. Wages dropped sharply in the aftermath of the crisis, and since then employment and wage growth have been moderate, with a significant portion of the labour force employed in the informal sector. Indonesia's labour market is known to be among the region's as well as the world's most inflexible labour markets, with hiring and firing regulations further tightened in the 2003 Manpower Law. However, considering that 63% of the employed workforce works in the informal sector, and that only 20% of workers in the formal sector report working with a contract, it fails to protect the most vulnerable workers (World Bank 2010)[18].

Table 1 presents some basic descriptive statistics of the sample in 2007. The average age in 2000

[12]Indonesia's administrative levels are provinces (*provinsi* or *propinsi*) which are divided into districts, which are further divided into subdistricts. Districts can be cities (*kota*) or regencies (*kabupaten*). For the purpose of this study, *cluster* or *community* refers to the IFLS communities, which are the original 321 communities plus the communities of mover households.

[13]In particular when studying the consequences of natural disasters, a low attrition rate is a pre-requisite.

[14]They live in 127 of the original IFLS communities, 224 communities of split-off households, and across 84 districts.

[15]The results are robust to including yearly wages for those individuals who have missing monthly wages but we prefer to not aggregate across these different recall spans.

[16]We top code individuals who reported working more than a total of 126 hours per week to 126 (assuming a maximum work load of 18 hours per day for 7 days a week) and only include individuals with positive earnings in both years.

[17]Following Thomas et al. (1999) we use a province-specific price deflator that is based on the price indices reported by Indonesia Statistics for 45 cities in Indonesia (43 cities until 2003), matching the BPS cities to the IFLS provinces and using a simple average of the price indices for provinces with more than one city. Thomas et al. (1999) construct an alternative measure for inflation based on the price data collected in the IFLS community questionnaire and find that rural inflation was 5% higher than urban inflation; therefore, they decide to further inflate prices for rural residents. Given that the period between 2000 and 2007 has noted a far more stable price environment than pre-crisis, we only use the BPS price data. As will be explicit in the next section which outlines the empirical framework, we take first differences to account for location specific time invariant effects; further, we include a dummy variable if the household lives in an urban area to account for differential wage growth.

[18]For a detailed analysis of the Indonesian labour market see World Bank (2010).

Table 1: Sample Characteristics

	2000	2007	Definition
Basic Characteristics			
Age	36.031		Age of respondent in 2000
Gender	0.633		Male=1, Female=0
Primary	0.482	0.478	=1 if highest level of school attended is elementary school, islamic elementary school (Madrasah Ibtidaiyah) or islamic school (Pesantren)
Secondary	0.356	0.346	=1 if highest level of school attended is junior/senior high, or islamic junior/senior high school (Madrasah Tsanawiyah, Madrasha Aaliyah)
Tertiary	0.106	0.118	=1 if highest level of school attended is university education
Urban	0.493	0.554	=1 if household lives in an urban location
Employment Category			
Self-employed	0.403	0.539	=1 if self-employed, self-employed with unpaid family worker/temporary worker and casual workers
Firm Owner	0.018	0.029	=1 if self-employed with permanent worker(s)
Government Worker	0.089	0.096	=1 if government worker
Private Worker	0.490	0.336	=1 if private worker
Employment Sector			
Agriculture	0.18	0.193	=1 if individual works in agriculture, forestry, fishery and hunting
Construction	0.088	0.075	=1 if individual works in construction, mining, electricity and gas, water
Manufacturing	0.203	0.179	=1 if individual works in manufacturing
Commercial Services	0.302	0.321	=1 if individual works in wholesale, retail restaurants and hotels; transportation, storage and communications; finance, insurance, real estate and business services
Social Services	0.227	0.231	=1 if individual works in social services
Contract Features			
Contract		0.062	=1 if individual works with a contract
Union		0.100	=1 if individual is member of a labour union or a business association
N	2471		

is 36 years. Slightly less that half of the respondents have at most primary education, and for about 35% the highest level of education is secondary school. Between 11 and 12% has tertiary education. About half of the sample lives in urban communities. The Indonesian labour market is highly segmented, with about half of the individuals self-employed. Their share has even increased between 2000 and 2007, so that in 2007 they constitute the single largest category of employment, followed by private workers, government workers and firm owners. In terms of the sectoral distribution of workers, commercial services employ about a third of the sample, followed by social services, manufacturing, agriculture and construction[19]. The high level of informality in the Indonesian workforce

[19]There is substantial overlap between categories of employment and sectors. In 2000, about half of the workers in agriculture are self-employed, with the other half being wage workers. Almost all workers in the construction sector are wage workers. About 28% of workers in the manufacturing sector are self-employed and 69% of workers are wage workers. Employment in commercial services follows the opposite pattern: 69% of workers are self-employed, and 27% of workers are wage workers. The largest group in social services are wage workers with 46%, followed by government workers with 32% and self-employed with 20%. Firm owners comprise between 1-2% of each of these categories.

also becomes apparent when noting that only 6.2% of workers in our sample have a written contract. About 10% of workers are members of a union.

Differences in median levels of income and median growth are illustrated in tables 20 and 21 in the Appendix. Table 20 shows that government workers enjoy the highest hourly wages in both years, about four to five times the hourly wages of self-employed and wage workers and about one quarter more than firm owners. Given that firm owners work about 50 hours per week compared to government employees who work 37 hours per week, monthly wages are fairly similar for government workers and firm owners in 2000 but substantially lower for firm owners in 2007. Self-employed have the lowest level of wages in both rounds, and the gap between wages of self-employed and wage workers has widened. Columns (4) and (5) show median growth rates of log of hourly and monthly wages, where the top panel conditions on the category of employment in 2000 and the bottom panel conditions on the category of employment in 2007. The highest growth of real wages has been enjoyed by government workers and private sector workers, while firm owners and self-employed either had very moderate growth or negative growth in the period between 2000 and 2007. Table 21 shows that differences in median hourly and monthly earnings are smaller across sectors. Both in 2000 and 2007, employees in the social services sector have the highest hourly and monthly wages, followed by the construction, manufacturing, commercial services and agriculture sector. Median wage growth was lowest or negative in the agriculture sector and highest in the social services sector, which is where 89% of government employees work.

We use two sources of data to measure the exposure to the earthquake. First, we use data from the Desinventar database for Indonesia, maintained by the Indonesian National Board for Disaster Management (BNPB[20]). The database contains information on the type of disaster, geographical location, as well as information on its effect on human life, property damage and on infrastructure. As a measure for the strength of a disaster, we use the number of destroyed houses[21]. The earthquake in Yogyakarta accounts for a significant proportion of deaths and houses destroyed caused by earthquakes in Indonesia between 1972-2009. About 48% of deaths by earthquakes and about 27% of houses destroyed by earthquakes were caused by the Yogyakarta earthquake[22].

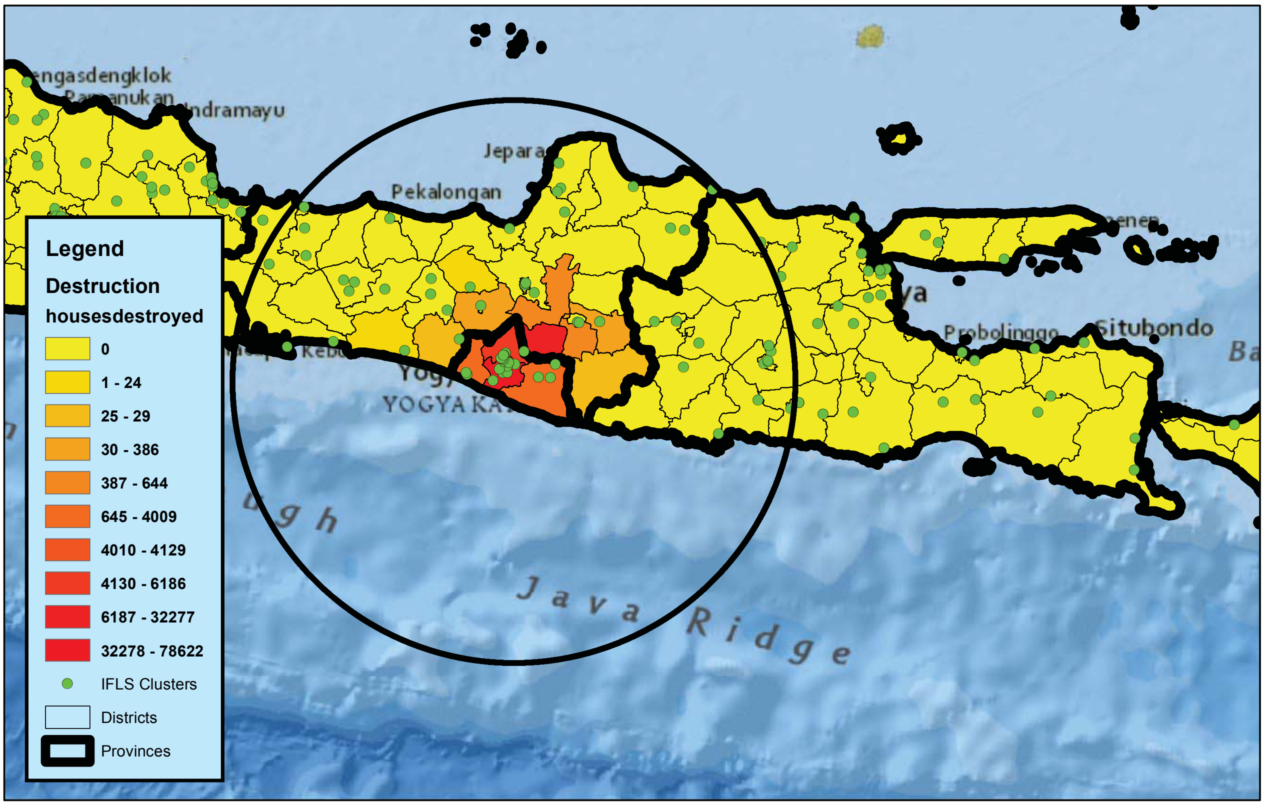
Figure 2 zooms into Java and shows the epicentre of the Yogyakarta earthquake. The green circles represent the locations of the original IFLS clusters; districts (provinces) are indicated by the thin (thick) boundaries. The different colours indicate the level of destruction caused by the earthquake in each district, ranging from no destruction (yellow) up to 78,622 houses destroyed (dark red). We use an individual's location in 2007 to link the IFLS data with the earthquake data.

[20]The full name is Badan Nasional Penanggulangan Bencana.

[21]We use data from Indonesia's Statistical Agency for the population in each district in 2005 to account for differences in population density across districts.

[22]The number of houses negatively affected by the earthquake varies across reports from 154,000 houses destroyed and 260,000 damaged (BAPPENAS 2006), 280,000 houses destroyed (Java Reconstruction Fund 2007), 270,000 houses heavily damaged (International Recovery Platfrom 2009). According to the Desinventar database, there were 129,798 houses destroyed and 172,854 houses damaged. To ensure that our results are not driven by reporting bias, we also use a measure of the earthquake that is independent of reporting and relies on exogenous characteristics of the earthquake.

Figure 2: Yogyakarta Earthquake, 27 May 2006 at 05:53:58 AM



Source: ArcGIS 10; data from US Geological Survey and IFLS communities.

Second, we use data on the characteristics of the ground shaking produced by the Yogyakarta earthquake from the United States Geological Survey[23]. In particular, we use the shakemap which is an exogenous measure calculated based on peak ground velocity and peak ground acceleration. While an earthquake has only one magnitude and one epicentre, it leads to a range of intensities in the area around the earthquake[24]. The shakemap shapefile indicates instrumental intensities of the earthquake using the modified mercalli intensity scale[25]. Compared to the magnitude and depth of the earthquake at the epicentre, the instrumental intensity is a more useful measure of the consequences of the earthquake in the area surrounding the epicentre. In contrast to the traditional mercalli intensity measure and other measures of the level of destruction of an earthquake, the advantage of the instrumental intensity scale is that it is derived uniquely from exogenous characteristics of the earthquake and not from observations and damage reports. It is therefore a more exogenous measure of the earthquake than any reported measure.

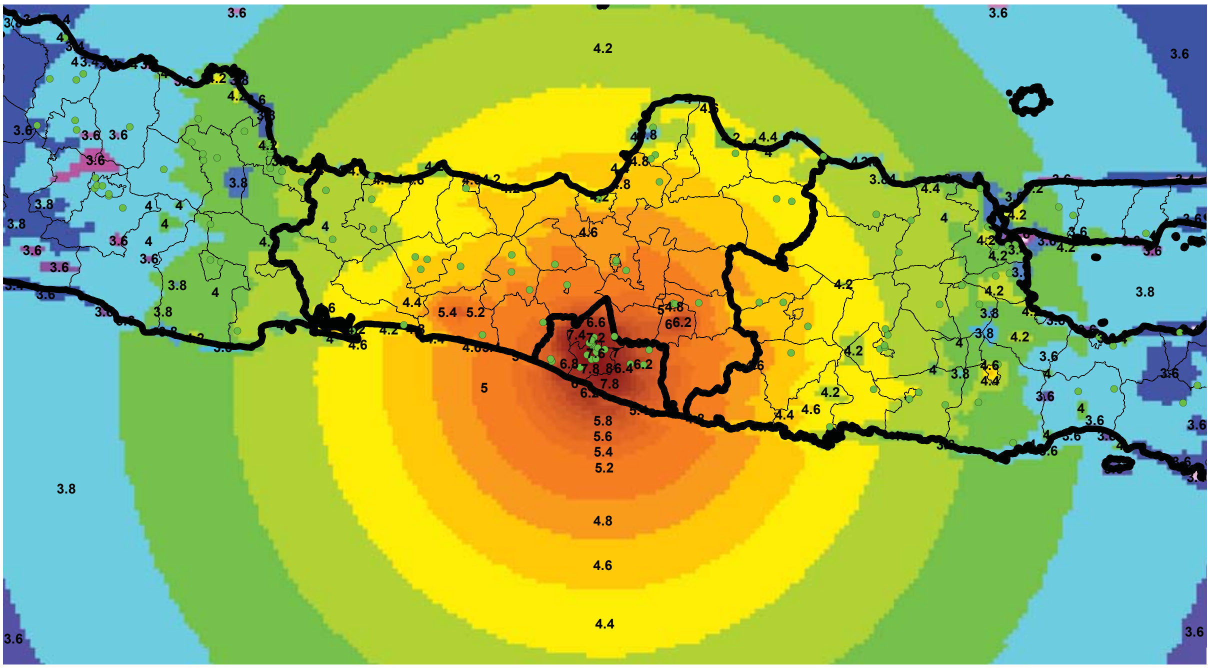
[23]There are different approaches in the literature to measure the effect of earthquakes. Yang (2008) constructs two distance bands from the epicentre of the earthquake, where he defines 'near' quakes as those within 100 kilometres of the epicentre of the first earthquake and 50 kilometres of epicentre of the second. Those in 'middle distance' to quakes are those within 125 kilometres of first epicentre and 75 kilometres of second epicentre (but not in 'near' area). Halliday (2006) constructs an index of destruction based on various damage measures. The methodology employed in Baez and Santos (2008) is most directly related to ours as they exploit the exogenous characteristics of the earthquake.

[24]For example, the Richter scale is a scale that measures the magnitude of the earthquake at the epicentre. To measure the intensity of an earthquake in the vicinity of the epicentre, the modified mercalli scale or the Rossi-Forrel scale are common.

[25]Figure 6 in the appendix overlays the map in figure 2 with the shakemap shapefile and shows that the contours for higher instrumental intensity correlate with the level of reported destruction.

We use ArcGIS 10.0 to link the shakemap with the household data. The instrumental intensity contour polygons are provided in 0.2 intensity units. We convert the polygons into a raster of 0.28 degrees (pixels of approximately 3.2 km by 3.2 km) and extract the modified mercalli intensity scale measure for each community[26]. The raster conversion is shown in figure 3[27].

Figure 3: Modified Mercalli Intensity Map, Yogyakarta Earthquake



Source: ArcGIS 10; data from US Geological Survey and IFLS communities.

Given the vast size of Indonesia and heterogeneity in terms of geography, income and population density it would not be suitable to use all individuals of the IFLS sample outside a certain radius as a comparison group. Rather, to have a sample that is very comparable to the treatment group we limit the sample to individuals in clusters or districts with an exposure of at least 3.7 on the mercalli scale, thereby within a radius of about 380 km of the earthquake's epicenter[28]. The geographic area covers the provinces West Java, Central Java, Yogyakarta Province and East Java which are densely populated[29].

[26]For individuals who moved outside their original clusters into a non-IFLS cluster we don't have the exact GPS location, but know their district of residence. We therefore extract the average mercalli intensity measure for each district using the zonal statistics tool, which is in line with the literature using spatial data. For example, Nunn and Puga (2012) compute the average ruggedness of a country by averaging over a grid level index of ruggedness. Burgess et al. (2012) compute the number of pixels which were deforested in each province in Indonesia using satellite information on deforestation.

[27]figure 7 in the appendix shows the map zoomed into the epicentre of the earthquake. Table 22 in the appendix shows the number of houses destroyed and damaged in districts affected by the earthquake from the Desinventar database as well as the mercalli intensity scale and the population in 2005. High damage corresponds to high values of the mercalli scale. In the whole data set, the pairwise correlation of these two measures of earthquake intensity is 0.78 with a p-value of 0.000.

[28]We show that our results are robust to changes in the comparison groups.

[29]Mean district level population in these 4 provinces in 2008 was 1,109,765 with a standard deviation of 677,366.7. The smallest district is Kota Mojokerto with a population of 114,804 and the largest district is Bogor with a population of 4,219,324.

3 Conceptual Framework

This section sets out a simple framework outlining the effects a natural disaster can have on local labour markets. It combines approaches from the labour economics literature on local labour markets (Moretti 2010a; Moretti 2010b), work on sectoral labour market dynamics (Carrington 1996; Keane and Prasad 1996; Kline 2008) and the predominantly macro-focused literature on Dutch-disease type of effects (Corden and Neary 1982; Corden 1984; Collier and Gunning 1999).

We consider the effect of a destructive natural disaster on local labour markets. Assume that the natural disaster is a rapid-onset event such as a hurricane or an earthquake which has an immediate effect that wears off fairly quickly[30]. Neither firms nor workers can predict the event. Therefore, firms can not ex ante expand or contract, or change their capital-labour ratios in order to reduce adjustment costs once the disaster strikes. We first look at the direct effects on demand and supply of labour. We then examine how the effects of the disaster on physical capital might affect the labour market. Finally, we examine how heterogeneity across sectors and categories of employment could matter.

A most immediate and direct effect of the earthquake is a decrease in the labour supply due to deaths and injuries. If labour supply is limited and capital was held constant, this would increase wages. Given the relatively limited number of deaths as a proportion of the total population and the substantial level of unemployment in Indonesia we would not expect a strong wage response to the decrease in labour supply[31]. In the reconstruction period, inflows of aid money are expected to increase the demand for local labour, as long as some of the labour employed to deliver goods and services is local.

Alongside destruction of human lives, the earthquake also destroys physical capital such as private and public buildings, equipment and infrastructure, such as roads and bridges, thereby reducing the physical capital stock. How this affects the demand for labour depends on the scale of destruction as well as substitutability between capital and labour in the production process. Considering a representative firm whose machineries have been destroyed but who can substitute machinery with labour to some extent, this would increase the demand for labour. Horwich (2000) argues when discussing the aftermath of the Kobe earthquake in Japan, as long as human capital remains, production processes will be re-optimised, relying on higher levels of labour or energy, for example[32]. On the other hand, if capital and labour are perfect complements, the drop in the capital stock will decrease the demand for labour. In the reconstruction phase the capital stock is going to be rebuilt leading to an increase in the demand for structures and equipment. If labour is a complement to capital in the reconstruction of the capital stock, the accelerated activity in reconstruction would

[30]The opposite is what the disaster literature refers to as 'slow-onset disasters' such as a drought (Benson and Clay 2004). Potential behavioral responses by individuals and governments are very different for these two types of disasters.

[31]Out of the 12 districts which recorded houses destroyed by the earthquake, the number of deaths accounted for 0.05% of the total population of these 12 districts in 2005.

[32]Labour could work longer hours, and energy could be used more intensively to heat buildings despite holes in the structure.

exert an upward shift in labour demand[33].

Given the characteristics of the Indonesian labour market presented in the previous section, it is also important to think through the effects a natural disaster could have on different employment categories. Informal workers might suffer larger losses from the shock as they lack employment protection, but they might also be more flexible in shifting to different sources of employment and taking advantage of arising opportunities. The effects are therefore theoretically ambiguous.

The effects are also likely to differ across sectors. We would expect the reconstruction efforts to be concentrated in the construction and the service sector. If labour is a complement to capital there will be an increased demand for workers in these sectors. Depending on whether there is sufficient surplus labour, this will or will not increase wages in these sectors to facilitate shifts. Due to the higher degree of tradability of manufactured goods, we would expect the manufacturing sector to suffer relatively more from supply disruptions due to the destruction of infrastructure in the immediate aftermath of the disaster. In the medium term, being relatively capital intensive, firms possibly substitute capital with labour until the capital stock is restored. The destruction of firms' capital stocks by the natural disaster might also affect firms' optimal capital labour ratios. If the natural disaster raises firm owners' expectations over the occurrence of another natural disasters in the future, this might lower the expected return to physical capital and raise the expected return to human capital, leading to a change in firms' optimal capital-labour ratios. When replacing their capital stock, firms might upgrade to newer technologies which might raise the productivity of workers.

Finally, the effect on the agricultural sector is likely to depend strongly on the level of destruction of harvests and agricultural technology (such as irrigation canals) as well as infrastructure. If harvests are destroyed that would imply a downward shift in the demand for labour that would otherwise have been hired in the harvest season. The destruction of infrastructure could also affect the tradability of goods and services leading to goods and services which were previously tradable suddenly becoming non-tradables. We would expect this natural "trade restriction" to lead to downward pressure in prices of food in surplus areas, and upward pressure on prices in deficit areas (Dercon 1995). Given that wages are lowest in the agricultural sector as discussed in the previous section, it is likely that agricultural workers are willing to take up employment opportunities in other sectors if they became available to them. In summary, the combined effect of the destruction and reconstruction shock are theoretically ambiguous and are therefore an empirical question.

4 Identification and Estimation

We start by outlining our methodology to investigate the effect of the earthquake on wage growth and heterogeneity in wage growth across categories of employment and sectors; before presenting the results, we also test for potential biases due to selection, migration and attrition. Our identification strategy relies on the exogenous nature of the earthquake. Let's denote the first round of the survey (July-December 2000) as $t = 1$ and the second round of the survey (October 2007-July

[33]This is the equivalent of what Corden (1984) would refer to as the booming sector.

2008) as $t = 2$. We then assume that individual i's wages in $t = 1$ and $t = 2$ are as follows

$$\ln y_{i1} = a_1 + \boldsymbol{X}'_{i1}\,\boldsymbol{c}_1 + \boldsymbol{S}'_{i1}\,\boldsymbol{d}_1 + \boldsymbol{Z}'_{i1}\,\boldsymbol{e}_1 + (f_{p1} + g_i + u_{i1}) \tag{1}$$

$$\ln y_{i2} = a_2 + b_2\,H_i + \boldsymbol{X}'_{i1}\,\boldsymbol{c}_2 + \boldsymbol{S}'_{i1}\,\boldsymbol{d}_2 + \boldsymbol{Z}'_{i1}\,\boldsymbol{e}_2 + (f_{p2} + g_i + u_{i2}) \tag{2}$$

where

y_{i1} is the wage observed in $t = 1$.

y_{i2} is the wage observed in $t = 2$.

H_i is the time-invariant measure of destruction through the earthquake[34].

$\boldsymbol{X}_{i1}$ is a vector of individual or household characteristics in $t = 1$.

$\boldsymbol{S}_{i1}$ is a vector of dummy variables indicating the sector of employment in $t = 1$.

$\boldsymbol{Z}_{i1}$ is a vector of dummy variables indicating the category of employment in $t = 1$.

f_{p1} and f_{p2} are dummy variables for provinces.

g_i is a time invariant individual fixed effect.

u_{i1} and u_{i2} are idiosyncratic shocks.

First differencing then gives

$$\Delta \ln y_{i2} = \Delta\, a_2 + b_2\,H_i + \boldsymbol{X}'_{i1}\,\Delta\boldsymbol{c}_2 + \boldsymbol{S}'_{i1}\,\Delta\boldsymbol{d}_2 + \boldsymbol{Z}'_{i1}\,\Delta\boldsymbol{e}_2 + (\Delta f_{p2} + \Delta u_{i2}) \tag{3}$$

which removes the individual fixed effect g_i and can be rewritten as

$$\Delta \ln y_{i2} = \alpha + \beta\,H_i + \boldsymbol{X}'_{i1}\,\boldsymbol{\gamma} + \boldsymbol{S}'_{i1}\,\boldsymbol{\delta} + \boldsymbol{Z}'_{i1}\,\boldsymbol{\theta} + (\phi_p + \varepsilon_{it}) \tag{4}$$

presenting our baseline specification. To measure the effect of the earthquake shock, our main measures are the number of houses destroyed per population in 2005 and the mercalli measure of earthquake intensity. Individual and household characteristics include age, age squared, education, urban location, gender and hours worked; sectoral dummy variables indicate whether the individual is employed in agriculture, construction, manufacturing, commercial services (base category) or social services; the category of employment is denoted by dummy variables for whether the individual is self-employed (base category), firm owner, employed by the government or in the private sector. We also control for the time span between the earthquake on 27 May 2006 and the date of the household interview[35]. The median household was interviewed 631 days after the earthquake, with the first households interviewed 550 days after the earthquake, and the last households interviewed 760 days after the earthquake. Additionally, we add month dummies for both the surveys

[34] Alternatively, we could also write down the model including $H_{i1} = 0$ in $t = 1$ for all households and H_{i2} in $t = 2$ to measure the earthquake. Given that the shock only occurs between $t = 1$ and $t = 2$ we prefer to make this explicit by denoting it as a time-invariant variable.

[35] If a household interview took place over several days, we use the first date of the interview.

in 2000 and 2007 to account for the fact that wage growth between 2000 and 2007 might depend substantially on the season and therefore timing of the interviews.

As we condition on baseline characteristics in equation (2), equation (4) differs from a standard panel fixed effects model in that we condition on lagged characteristics. We prefer this specification for several reasons: first, the control for baseline characteristics in equation (2) is particularly relevant for variables that capture responses to the earthquake, such as sectoral shifts that are induced by the earthquake which are correlated with wages, biasing our estimate of d_2. It is similar to what Angrist and Pischke (2008) call 'bad controls', in that controlling for the sector of employment in period 2, or taking differences in sectoral dummies, would capture part of the response to the earthquake. Recognizing that this is our preferred specification, we also estimate the model using a fixed effects specification, and the results are robust.

Second, the potential benefit of fixed effects or first differences specification comes at the cost of identifying parameters solely relying on individuals who shift across sectors in a treatment area. Third, our main question is what the effects of a large shock are, conditional on having been employed in a certain sector. Finally, the identifying assumption in our model is that $E(\varepsilon_{it}|H_i, \boldsymbol{X}_{i1}, \boldsymbol{S}_{i1}, \boldsymbol{Z}_{i1}, \phi_p) = 0$, so that education, age, location, sector of employment and category of employment in 2000 are not correlated with unobservables determining wage growth between 2000 and 2007. It is not difficult to come up with a violation of this assumption, for example, more educated individuals being more able to cope with shocks to wage growth, and thereby having higher wage growth. However, we find this assumption still more convincing than assuming that current individual labour market characteristics are uncorrelated with current unobservables determining wages once time-invariant individual characteristics are controlled for, which is assumed in a standard fixed effects model. We nevertheless show that our results are virtually unchanged when we estimate the model as a fixed effects specification or a diff-in-diff specification.

Further, an important choice in the empirical specification relates to the inclusion of a lagged dependent variable, where the obvious trade-off between endogeneity due to the inclusion of an endogenous variable and endogeneity due to omitted variables is the central issue. As a robustness check, we therefore also estimate model (4) with a lagged dependent variable, and instrumenting for the lagged dependent variable using earnings in 1997[36].

An immediate concern given the labour market structure is whether earthquakes are impacting self-employed and wage-employed individuals similarly. We therefore use the base model defined in equation (4) and interact the category of employment with the measure of destruction and estimate the following model

$$\Delta \ln y_{i2} = \alpha + \beta H_i + \boldsymbol{X}'_{i1}\boldsymbol{\gamma} + \boldsymbol{S}'_{i1}\boldsymbol{\delta} + \boldsymbol{Z}'_{i1}\boldsymbol{\theta} + (H_i * \boldsymbol{Z}_{i1})'\boldsymbol{\lambda} + (\phi_p + \varepsilon_i) \tag{5}$$

[36] We use zero for individuals for whom we do not have a wage in 1997; alternatively, we have also estimated the model only with the 1,499 individuals who have positive wages in all of the three rounds, and the results are the robust.

and then test whether $\boldsymbol{\lambda} = 0$ to assess whether the earthquake had a different effect depending on the sector of employment.

To determine heterogenous sectoral effects of the earthquake shock, we use the base model defined in equation (4) and interact the sector of employment in 2000 with the earthquake shock

$$\Delta \ln y_{i2} = \alpha + \beta H_i + \boldsymbol{X}'_{i1}\boldsymbol{\gamma} + \boldsymbol{S}'_{i1}\boldsymbol{\delta} + \boldsymbol{Z}'_{i1}\boldsymbol{\theta} + (H_i * \boldsymbol{S}_{i1})'\boldsymbol{\xi} + (\phi_p + \varepsilon_i). \tag{6}$$

The coefficient vector $\boldsymbol{\xi}$ indicates whether there is heterogeneity in the effect of the earthquake depending on the sector of employment of the individual before the earthquake.

5 Empirical Results and Discussion

We start by presenting the base results in which we investigate overall wage growth, as well as heterogeneity with regard to the sector and category of employment of the individual before the earthquake. We then discuss possible mechanisms.

5.1 Base results

Table 2 shows the results for equation (4). Column (1) includes the number of houses destroyed per person and column (2) shows the log of the number of houses destroyed. For districts in which no houses were destroyed, we replace the variable with zero. The third column uses the mercalli intensity measure. The results show that households who were affected by the earthquake have on average significantly higher wage growth, and this result is robust to the measure of the earthquake shock.

Table 2: Dependent Variable: Changes in Log of Monthly Wages

	Houses Destroyed	Log Houses Destroyed	Intensity Measure
	(1)	(2)	(3)
Houses destroyed	4.450***		
	(1.105)		
Log Houses destroyed		0.053***	
		(0.014)	
Mercalli			0.14***
			(0.051)
Obs.	2471	2471	2471
R^2	0.071	0.07	0.069

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

For a one percentage point increase in the proportion of houses destroyed per population, wage growth was 3.9 percent higher. The coefficient on the log of houses destroyed is not deflated by population and indicates that for a 1 percent increase in the number of houses destroyed, wage growth was 0.05 percent higher. The third row uses the exogenous modified mercalli intensity scale and indicates that for a one unit increase in the shake intensity experienced by the individual, wage growth was on average 14% higher. As both, the number of houses destroyed and the log of houses destroyed are based on the same underlying destruction measure, we present the remainder of the results for the effect of housing destruction per population (denoted by ratio in the column header) as well as the modified mercalli intensity scale (denoted by mercalli in the column header)[37]. Table 23 in the appendix lists all explanatory variables except the month of interview dummy variables. The table shows that wage growth in construction and manufacturing was significantly lower than wage growth in commercial services. Wage growth was also lower for males illustrating that the gender wage gap is becoming smaller. Controlling for basic characteristics such as education, age, location, sector and category of employment wages were 40% higher for men at baseline in 2000. Wage growth is significantly higher for workers in urban areas. We do not find this result when looking at the cross sections in 2000 and 2007, but see the same effect when conditioning whether a worker was in an urban area in 2007. This suggests that the well documented urban wage premium operates in the sample through a higher growth rate rather than higher levels (Glaeser and Maré 2001). Wage growth is significantly faster for private sector workers and government workers compared to self-employed. Compared to a hypothetical worker in Yogyakarta unaffected by the earthquake shock, wage growth tends to be higher for workers outside Yogyakarta[38]. We do not find evidence for a significant wage effect dependent on the days between the earthquake and the survey. We have also experimented with higher order polynomials but this did not affect the results.

As the labour market is fragmented with a large proportion of individuals in self-employment, we now interact the earthquake measure with whether an individual is self-employed, employed by the government, or works in the private sector to determine whether the evolution of wage growth is different for individuals depending on their category of employment before the earthquake. Table 3 shows that there is a negative effect for government workers when using the destruction measure, but not when using the mercalli measure. There is no evidence, however, that self-employed individuals suffered lower wage growth after the earthquake.

Next, we interact the earthquake shock with the sector of employment of the individual in the period before the earthquake, taking commercial services as the base group. The results in table 4 suggest that the higher average wage growth is predominantly driven by workers in the agricultural sector obtaining higher wage growth compared to individuals employed in commercial services. This effect is significant at the 1% level for both earthquake measures as shown in columns (1) and (2). We add district dummy variables to account for differences in district level wage growth rates in column (3); this does not affect the coefficients nor the significance level. The last three rows show the p-values of hypothesis tests where the null hypothesis is that the coefficient on the earthquake-agriculture interaction term is equal to the other earthquake-sector interaction terms. The tests suggest that we can reject at the 10% level when using the destruction measure, and at the 1% level when using the mercalli measure, that these coefficient are equal to each other. When the

[37] We prefer houses destroyed per population to take into account population density.

[38] As we control for the exposure to the earthquake, the interpretation of the province dummies indicates differences holding earthquake exposure constant. As workers in Yogyakarta were all affected to varying degrees by the earthquake, the comparison group is a *hypothetical* worker unaffected by the earthquake.

Table 3: Dependent Variable: Changes in Log of Monthly Wages

	Houses Destroyed	Intensity Measure	Intensity Measure District FE
	(1)	(2)	(3)
Earthquake	4.702***	0.143**	0.035
	(1.336)	(0.059)	(0.125)
Earthquake*Firm Owner	0.199	0.009	0.05
	(5.039)	(0.103)	(0.106)
Earthquake*Government Worker	-3.168**	-.061	-.043
	(1.537)	(0.042)	(0.041)
Earthquake*Private Sector	0.146	-.002	0.021
	(1.468)	(0.04)	(0.038)
Obs.	2471	2471	2471
R^2	0.071	0.069	0.11

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 4: Dependent Variable: Changes in Log of Monthly Wages

	Houses Destroyed	Intensity Measure	Intensity Measure District FE
	(1)	(2)	(3)
Earthquake	1.902	0.096*	-.022
	(1.609)	(0.053)	(0.129)
Earthquake*Agriculture	9.161***	0.334***	0.301***
	(3.398)	(0.079)	(0.079)
Earthquake*Construction	2.493	0.087*	0.083*
	(1.937)	(0.049)	(0.049)
Earthquake*Manufacturing	4.258	0.027	0.031
	(2.616)	(0.062)	(0.064)
Earthquake*Social Services	1.754	0.035	0.049
	(2.484)	(0.044)	(0.044)
Obs.	2471	2471	2471
R^2	0.075	0.08	0.118
$H_0 : \xi_{agr} = \xi_{con}$	0.031	0.002	0.006
$H_0 : \xi_{agr} = \xi_{man}$	0.088	0.000	0.001
$H_0 : \xi_{agr} = \xi_{soc}$	0.012	0.000	0.001

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

earthquake is measured with the mercalli scale in columns (2) and (3), we also find some evidence that individuals working in the construction sector before the earthquake experience higher wage growth, but the coefficient is not significantly different from the coefficient on the interaction term between the earthquake and the manufacturing or social services sector[39].

[39] As part of the effect of category of employment and sector of employment might depend on the sector and category of employment before the earthquake, we have also estimated the model underlying table 3 omitting the control for baseline sectors of employment and the model underlying table 4 omitting the control for baseline category of employment; the results are very similar.

We have conducted an extensive number of robustness tests with regard to our estimation of standard errors, identification assumptions, variable construction and sample definitions; we briefly outline them here and refer the reader to the detailed discussion presented in Appendix A. We first estimate the results with Conley standard errors instead of clustered standard errors. Second, following Leamer (1983)'s suggestion, we estimate a range of alternative models to show that our results are robust to different identifying assumptions, such as a diff-in-diff specification, a fixed effects specification, a dynamic model and a dynamic IV model. We then test the robustness of our results by using hourly wages instead of monthly wages, different recall periods, limiting the households in the control group. To tackle concerns related to the measurement of wages in the agricultural sector, we first show that it is not the case that self-employed workers are driving the results and then estimate the base model of (4) using total household expenditure as the dependent variable and show that the positive effect exists when the household head was employed in the agricultural sector. We have also estimated the results including a self-reported measure of whether the household suffered death or major injuries due to an earthquake[40], controlling for any other disasters the household reports[41], using the exogenous mercalli measure as an instrument for the destruction measure, using the full sample of individuals aged between 15-85, and using the attrition adjusted cross sectional individual sampling weights provided by the IFLS which make the IFLS sample of individuals representative of the 2007 population of individuals living in the original 13 IFLS provinces. All these robustness tests show very consistent results. Finally, we checked for potential biases due to selection, migration and attrition.

5.2 Mechanisms

While the higher wage growth for individuals working in the construction sector is intuitive given the upward shift in labour demand in the construction sector in the aftermath of the earthquake, explaining the increase in wage growth for agricultural workers is less obvious. We now explore in more detail why we might find an effect on agricultural wages. Profit maximizing firms will set wages equal to a workers' marginal product of labour multiplied by the price. Higher wage growth could be due to (i) higher agricultural prices or (ii) an increase in the marginal product of labour. We now investigate these channels in turn.

5.2.1 Increase in Prices of Agriculture Goods

The price of agricultural products could have increased due to the disruption in trade or the destruction of harvests; to explore the effect of trade disruptions on prices, we sketch the effects in a simple two-period framework borrowing ideas from Samuelson (1952)'s discussion of spatial price equilibrium. We then test whether there is any evidence in the data that these channels contributed to faster wage growth for agricultural workers. Assume that there are communities with excess

[40]It is highly and significantly correlated with our earthquake damage (corr=0.76) and earthquake intensity (corr=0.83) measures.

[41]With 15% of the sample reporting the Yogyakarta earthquake it is the only big earthquake reported in this period in our sample. Other natural disasters that have been reported include 0.8% (17 households) reporting a Tsunami in Cilacap, 4% (113 households) in various districts reporting a flood (22 of those in Kota Surakarta), and 1 household in Kediri reporting a volcanic eruption.

demand for rice (net buyer communities) and communities which have excess supply (net seller communities), and the price for rice importing communities is equal to the producer price plus a transport cost. The earthquake might have increased transport costs for affected communities. It might also cause some communities to shift from being net exporters to being net importers due to destruction of harvests[42].

We first assume that the difference in autarchy prices of net seller and net buyer communities is larger than the increased transport cost so that communities continue to trade. The effect on price growth then depends on whether communities were net sellers or net buyers before and after the earthquake. We examine four types of communities, communities which shifted from being net sellers to being net buyers (SNB), communities which were always net buyers (ANB), communities which were always net sellers (ANS) and communities which shifted from being net buyers to being net sellers (SNS). Assume that the switch of SNB communities was caused either by a negative supply shock due to the earthquake (for communities which were affected by the earthquake), or due to an unobservable shock (for communities not affected by the earthquake), and is such that autarchy prices of the former net seller increase, which raises equilibrium prices.

We would expect the highest increase in prices to be faced by communities which shifted from being net sellers to being net buyers. These communities did not pay for transport costs before, experienced the shock to supply and now face the increased transport cost after the earthquake. The second largest price effect is for communities which were always net buyers, both before and after the earthquake. Since the price of rice they faced before the earthquake already included transport costs, the growth in the price is by the additional transport cost caused by the destruction of infrastructure and the effect of the shock to SNB communities. For communities who were always net sellers, we only expect to see increase in price caused by the shock to SNB communities, since they do not face the increased transport costs. Finally, we expect communities which shifted from being net buyers to being net sellers to experience a higher price due the shock to SNB communities, but this is counteracted by not having to pay for transport costs anymore.

We expect the order of the price growth effects to be $\Delta p_{SNB} > \Delta p_{ANB} > \Delta p_{ANS} > \Delta p_{SNS}$. In the limit, if trade networks are completely destroyed, communities turn into little island economies which do not trade anymore. In this case, we would expect a price drop for communities which were net sellers before the destruction, and an increase in the price for communities which were net buyers. We will keep the four groups for the empirical analysis to determine which of these scenarios is consistent with the data[43].

[42] According to International Recovery Platfrom (2009), 92% of damage in the agriculture sector was due to production losses, and 80% of damages to infrastructure occurred in provincial and district roads. As part of a Rapid Livelihoods Assessment the Food and Agricultural Organization (2007) conducted a survey shortly after the earthquake in a sample of 25 either most damaged or most vulnerable villages and found that about 40% of paddy, 23% of corn and 73% of vegetables were damaged or remained unharvested after the earthquake. However, in terms of value the damage and losses to the agricultural sector are 10% of the losses to the small and medium entreprise sector (BAPPENAS 2006). A report by the Java Reconstruction Fund (2007) suggests that damage to the agricultural sector through lost crop yields amounted to US$2.5 million. The destruction of 100 irrigation units led to about 5,000 hectares of land being without water supply.

[43] In what we discussed we do not explicitly account for general equilibrium effects of the destruction of transport

To test this mechanism, ideally we would have consumption, production and price data for a range of goods and services. In the data set, however, rice is the only good for which we have information on the level of prices per kg in both survey rounds, household level production and household level consumption. To proxy prices of agricultural goods, we therefore use information on rice prices from the community questionnaire of the IFLS survey[44].

We use the household questionnaire to get a measure of whether a community is a net set seller or a net producer of rice. From the household questionnaire we use farmers who record rice as the most valuable crop that the household farm produced for the market or for home consumption and aggregate the value of total production generated by the farm business (including produce for own consumption or giving to others) in the last 12 months at the community level. To measure total consumption, we aggregate the value of households' yearly consumption of rice (home-produced or bought from the market) at the community level. We classify the community as a net buyer if the ratio of total consumption over total production is larger than one in a particular period[45]; we then use this to define whether a community has always been either a net buyer or net seller, or whether it changed its net position[46].

Since we need at least a reasonable sample of households per cluster to estimate aggregate production, we exclude communities which are not original IFLS communities (who will have few households living there in each round) which results in a sample of 126 communities. We then estimate the effect of the earthquake on the change in the price of rice using the following regression:

$$\begin{aligned}\Delta \ln p_{j2} = & \pi_0 + \pi_1 H_j + \pi_2 SNB_j + \pi_3 ANB_j + \pi_4 ANS_j \\ & + \pi_5 SNB_j * H_j + \pi_6 ANB_j * H_j + \pi_7 ANS_j * H_j + \varepsilon_{j2}\end{aligned} \tag{7}$$

for community $j = 1, \ldots, N$, where

p is the price of rice per kg.

H is a measure of destruction through the earthquake.

SNB is equal to one if a community shifted from being a net seller to being a net buyer of rice

infrastructure on communities not affected by the earthquake. In the empirical section we relax this assumption by using the continuous mercalli measure for the earthquake.

[44]In 2000, up to three markets or sales outlets were visited to collect data on prices of basic goods. In 2007, interviewers collected prices from local markets, shops/stalls, and up to three informants were asked. For rice prices, the 2007 questionnaire records prices for high quality rice, average quality rice and low quality rice. Since we only have information on average quality rice in 2000, we use this variable to calculate prices. To calculate the price per kg, we multiply the price of a litre of rice by (1/0.89) and the price in grams by 1000. When the price was obtained by various sources, we calculate a simple average price over these sources.

[45]We also show the results with different cut-offs.

[46]Another method to investigate how the earthquake shock has impacted integration and trade would be to look at the conintegrating relationship between price series of different clusters (Dercon 1995; Varela et al. 2012). However, we are not aware that district level or community level rice price data for Indonesia exist and we were told by BPS that such data do not exist. For the case of rice, our data construction method based on community price surveys has the advantage that we can hold quality of rice constant by looking at the price of rice of average quality. Convoluting product quality and price effects is a common problem when analysing aggregate price series (Varela et al. 2012).

between 2000 and 2007/2008.

ANB is equal to one if a community was a net buyer of rice in both 2000 and 2007/2008.

ANS is equal to one if a community was a net seller of rice in both 2000 and 2007/2008.

5.2.2 Downward Shift in Labour Supply

The second channel through which agricultural wages could have increased is through a downward shift in labour supply in the agricultural sector, possibly due to job opportunities opening up in other sectors of the economy associated with reconstruction. To test this channel, we use the Indonesian Sub-National Growth and Governance data set which contains sectoral employment shares at the district level for the years 2001-2004 and 2007. The labour market data contained in the data set are computed from SUSENAS data, a large yearly national socio-economic survey which is representative at the district level. The individual questionnaire in the SUSENAS survey asks the employment sector of household members aged 10 and over. The employment share per sector is defined as the number of individuals in each district employed in a particular sector divided by the total working population in each district. We also include the number of individuals unemployed which are computed on the basis of employed individuals aged 15 and over divided by the total labour force which is defined as individuals working, temporarily absent from work but having a job, those who did not work but were looking for a job or were preparing for a job. As the labour market data for 2005 are missing and we do not have information on the exact timing of the survey in 2006, we compare changes in sectoral employment shares between 2004 and 2007 in earthquake affected and comparison districts. To estimate the impact of the earthquake on the share of individuals employed in each sector we use the following specification:

$$\Delta \ln prop_{d2} = \lambda_0 + \lambda_1 H_d + \varepsilon_{d2} \tag{8}$$

for district $d = 1, \ldots, N$, where

$prop$ is the proportion of individuals employed in a particular sector and the proportion of individuals unemployed.

H is a measure of destruction through the earthquake.

The dependent variable $\Delta \ln prop_{d2}$ refers to changes in the log of the proportion of individuals employed in a particular sector between 2004 and 2007. To address the correlation of the residuals of the sectoral share equations, we estimate the model as a system of seemingly unrelated equations. We test these two channels in turn.

5.2.3 Evidence on Mechanisms

Table 5 shows the effect of the earthquake on the change in log prices of rice at the community level. There is a significant and positive effect for both earthquake measures, so that communities which were affected by the earthquake had steeper growth in average rice prices. A 1 percent increase in the proportion of houses destroyed leads to a 1 percent higher growth rate in the price of rice,

Table 5: Dependent Variable: Changes in Log of Rice Price

	Houses Destroyed	Houses Destroyed	Intensity Measure	Intensity Measure
	(1)	(2)	(3)	(4)
Earthquake	1.030***	0.273	0.021*	-.0003
	(0.173)	(0.367)	(0.012)	(0.011)
Earthquake*Shift to Net Buyer		1.274*		0.049**
		(0.753)		(0.024)
Earthquake*Always Net Buyer		1.234		0.011
		(3.059)		(0.015)
Earthquake*Always Net Seller		-.003		0.022
		(0.481)		(0.024)
Shift to Net Buyer		0.006		-.216
		(0.063)		(0.158)
Always Net Buyer		-.047		-.098
		(0.037)		(0.091)
Always Net Seller		0.031		-.079
		(0.041)		(0.124)
Obs.	126	126	126	126
R^2	0.03	0.107	0.043	0.136

Notes: Robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

and a one unit increase in the mercalli measure leads 2.1 percent higher growth in the price of rice. However, this average effect possibly masks significant heterogeneity across communities. We test whether this effect is stronger for different types of communities. Columns (2) and (4) show the results where the omitted category is communities which were always net sellers. Indeed the effect is stronger for communities that became net buyers in the sample period. We do not find evidence for an average increase in prices across different types of communities. Communities which shifted from being net sellers to net buyers and were affected by the earthquake experienced about 5% higher growth in the price of rice for a one unit increase in the mercalli measure compared to communities which shifted to being net sellers. Appendix A shows robustness of this finding to varying cut-offs in the ratio of consumption over production. Another factor that is important to consider when discussing rice prices in this period is the import ban the Indonesian government imposed on rice in January 2004 (McCulloch 2008), and the possible interaction of the import ban with the earthquake. We would expect the effect of the import ban to depend on the exposure to imports. To test whether this is the case we compute the distance of our communities with cities as well as ports, and interact the distance in kilometres with the earthquake measure[47]. We find that prices grew faster for earthquake affected communities which are further away from cities for both earthquake measures, and similar results for ports when using the destruction measure.

Table 6 shows the results from the district level sectoral shares equation, where each row shows the effect of the earthquake shock on the change in the proportion of individuals employed in a particular sector. We include the log of the number of houses in the second column as an alternative measure as our level of observation now is the district. The growth in the district level share of the population employed in the agricultural sector decreased significantly when using our first two

[47] Appendix A discusses the data sources we use in more detail.

Table 6: Dependent Variable: Sectoral Shares

	Houses Destroyed	Log of Houses Destroyed	Intensity Measure
	(1)	(2)	(3)
Δ % Agriculture	-.535***	-.017**	-.0093
	(0.1373)	(0.0072)	(0.0068)
Δ % Construction	1.11***	.0200***	.0128**
	(0.1763)	(0.005)	(0.0053)
Δ % Manufacturing	-.048	-.0009	.0038
	(0.4267)	(0.0072)	(0.0066)
Δ % Commercial Services	-.417	.0027	-.0049
	(0.2786)	(0.0068)	(0.0070)
Δ % Social Services	-.0928	-.0042	-.0022
	(0.0990)	(0.0043)	(0.0031)
Δ % Unemployment	.159	-.0023	-.0006
	(0.1220)	(0.0042)	(0.0035)
Obs.	91	91	91

Notes: Coefficients from system of 6 seemingly unrelated regressions, indicating the effect of the earthquake on the change in the proportion of individuals employed in a particular sector for the three different earthquake measures; robust standard errors in parentheses; *, **, *** denote significance at 10%, 5% and 1% levels.

measures in column (1) and (2), implying that a 1% increase in the proportion of houses destroyed leads to a 0.54% lower growth in the percentage of individuals employed in agriculture. The effect is less precisely estimated when using the mercalli measure. There is also a strong and significant effect on the construction sector across the three measures. For example, a one percent higher proportion of houses destroyed during an earthquake led to a 1.1% higher growth rate in the proportion of individuals employed in construction[48].

It is important to examine how these two proposed mechanisms might interact. Higher price growth in agriculture due to trade limitations and the resulting higher wage growth would, if anything, draw workers back into agriculture, thereby biasing upwards λ_1 in the agricultural shares equation of specification (8). On the other hand, it is possible, that the higher growth rate in the price of rice is also caused by the labour shifts out of agriculture, rather than trade restrictions and changes in output.

If earthquakes lead to job creation outside the agricultural sector, and workers previously employed in agriculture take up job opportunities outside agriculture, this leads to a downward shift in labour supply in the agricultural sector and therefore an increase in wages. We would also observe higher wage growth in earthquake affected communities, but this would be caused by the higher demand for labour in non-agricultural sectors. One way to test this is by including the change in the proportion of workers employed in each sector in equation (7). If all the effect is coming through sectoral shifts, the earthquake and net position of the community should not be significant anymore. The results are substantially the same when including sectoral changes, which suggests that we can

[48]The results are equivalent when we restrict the sample of districts to those in which a member of the IFLS sample lives.

not rule out that trade limitations and damage to infrastructure had an effect.

The results therefore suggest that the increase in wages in the agricultural sector in the aftermath of the earthquake was driven by a combination of sharper increases in the price of rice, in particular for communities which shifted from being net producers to net purchasers as well as shifts out of the agricultural sector, thereby raising the marginal product of labour of agricultural workers.

6 Conclusion

This paper explored how natural disasters affect labour markets, more specifically, wage growth across employment categories and sectors as well as changes in the sectoral composition of the labour force. Our identification relied on the exogenous nature of a large earthquake hitting Yogyakarta, Indonesia, on 27 May 2006. We used a panel of individuals from the Indonesia Family Life Survey living in the vicinity of the earthquake, and linked these with data on district level housing destruction, the modified mercalli intensity scale of the earthquake which takes into account peak ground velocity, peak ground acceleration and the topology of the region; data on community level rice prices and district level employment indicators.

We found that labour markets are remarkably resilient against such a large shock and on average wage growth was even higher in earthquake affected regions. We did not find strong evidence for differences in the effect of the earthquake according to whether individuals are self-employed, firm owners, government workers or employed in the private sector. Given that these employment categories have different levels of job protection and regulations, this result is rather surprising. However, we did find substantial heterogeneity with respect to the sectoral evolution of wages. Individuals who worked in the agricultural sector in areas that were strongly affected by the earthquake enjoyed a substantially higher earnings growth compared to individuals working in the commercial services sector, who nevertheless do not have any negative earnings growth effects. This suggests that local labour markets are fairly segmented and mobility is limited. In the agriculture sector this is likely to be the case since land as a factor of production is immobile, many farms are family farms, and monitoring of labour is relatively difficult in this sector. The result is robust to a range of specifications relying on alternative identifying assumptions compared to our preferred specification, including a differences-in-differences specification, fixed effects, a dynamic specification and a dynamic instrumental variables specification. A range of measures of the intensity of the earthquake shock and varying control groups also produce very consistent results.

We proposed two mechanisms for this result. First, the destruction of infrastructure led to increases in the price of food, particularly in areas which are net consumers of food. Second, a downward shift in the supply of labour due to fatalities and injuries and an increase in the demand for labour in sectors producing non-tradables in the aftermath of the disaster drew workers out of the agricultural sector (the low-wage sector) into higher-wage non-tradable sectors, leading to a rise in the marginal product of labour and wages in the agriculture sector. We find evidence for both mechanisms. The earthquake led to higher growth in the price of rice. We also show that growth of rice prices was higher in communities which switched from being net producers to being net consumers. Employment contracted in the agricultural sector and expanded in the construction sector in the aftermath of the earthquake. This suggests that both these effects resulted in higher wage growth for agricultural workers.

Even though this paper provided evidence on a natural disaster in Indonesia, the findings are relevant for other lower middle income countries as well, and suggest that efficient responses to large scale shocks can even lead to positive effects on the evolution of wages. As the response to the earthquake has been regarded as fast and efficient, this finding resonates with Kahn (2005) who finds that institutional quality can mitigate the adverse effects of natural disasters. But since this paper provided evidence on one particular natural disaster in Indonesia, further research in the following areas is still missing. First, how do local labour markets, in different contexts, respond to large scale shocks. For example, what type of labour market institutions are helpful in protecting wages and which institutions limit flexibility of labour. Second, how policy responses differ across contexts. To answer this question, an avenue for further research would then be to separately identify the effect of the destruction and the reconstruction shock, which we were not able to do in this paper. Finally, in this study we focused on the short to intermediate term effects. Longer post-disaster time series data on earnings would allow us to investigate longer wage dynamics to test whether the effects we find are transitory or persistent. Given that the propensity of natural disasters is expected to rise, and with rapid urbanization the consequences are going to be larger, all these become increasingly important questions.

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APPENDIX

A Robustness

A.1 Conley Standard Errors

When analysing a big shock like an earthquake, one needs to be concerned about spatial dependence between observations. We always cluster standard errors by sampling cluster and the coefficients on the agriculture interaction in table 4 have small standard errors; we still need to make sure that this is not due to biased estimation of standard errors. We therefore also estimated the standard errors using Conley (1999)'s method which adjusts the estimated covariance matrix to allow for spatial correlation. We select a cut-off value of 0.25 decimal degrees (about 30 km) in each direction over which the correlation is assumed to decrease linearly with distance and after which the correlation is set equal to zero. Split-off households are assigned the coordinates of the centroid of the district polygon, as we do not have their exact coordinates. Table 7 compares the two methods and shows that the method to cluster standard errors does not significantly affect the results. If anything, Conley standard errors are slightly smaller than simple clustered standard errors. Both do not affect our results. However, Conley standard errors have the disadvantage that we impose that all split-off households live in the centroid of the polygon and thereby ignore potentially different correlation among individuals living in the same cluster, which is likely to lie outside the polygon centroid. Given the similarity in the size of the standard errors, for the remainder of the paper, unless specified otherwise, we present standard errors clustered at the level of the sampling cluster.

Table 7: Dependent Variable: Changes in Log of Monthly Wages

	Houses Destroyed	Intensity Measure
	(1)	(2)
Earthquake	1.902	0.096
Clustered s.e.	(1.609)	(0.053)*
Conley s.e.	(1.248)	(0.049)**
Earthquake*Agriculture	9.161	0.334
Clustered s.e.	(3.398)***	(0.079)***
Conley s.e.	(2.300)***	(0.076)***
Earthquake*Construction	2.493	0.087
Clustered s.e.	(1.937)	(0.049)*
Conley s.e.	(1.707)	(0.042)**
Earthquake*Manufacturing	4.258	0.027
Clustered s.e.	(2.616)	(0.062)
Conley s.e.	(2.498)*	(0.054)
Earthquake*Social Services	1.754	0.035
Clustered s.e.	(2.484)	(0.044)
Conley s.e.	(2.027)	(0.038)
Obs.	2471	2471

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

A.2 Model Specifications

We now show that the increased wage growth effects in the agricultural sector are robust to a number of different specifications. Table 8 shows equation (6) using hourly wages as the dependent variable. In Table 9 we replace missing monthly wages if individuals reported last year's wages or profits by yearly wages or profits divided by 12; the results are substantively equivalent, but we prefer to refrain from aggregating across different recall periods. We also vary comparison groups to test

Table 8: Dependent Variable: Changes in Log of Hourly Wages

	Houses Destroyed	Intensity Measure	Intensity Measure District FE
	(1)	(2)	(3)
Earthquake	2.122	0.056	-.189
	(2.219)	(0.064)	(0.147)
Earthquake*Agriculture	6.605*	0.309***	0.293***
	(3.613)	(0.086)	(0.09)
Earthquake*Construction	3.805	0.116*	0.12**
	(2.835)	(0.06)	(0.058)
Earthquake*Manufacturing	3.271	0.004	0.007
	(3.260)	(0.077)	(0.079)
Earthquake*Social Services	2.339	0.032	0.048
	(3.010)	(0.053)	(0.056)
Obs.	2469	2469	2469
R^2	0.051	0.055	0.095

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

whether different cut-offs in the modified mercalli scale limiting the comparison group affects the results. Columns (1)-(3) limit the sample to individuals with an exposure above 3.8, 4.1 and 4.2 on the mercalli scale. Table 10 indicates that the results are robust to different cut-offs, although the positive effect on the construction sector disappears when limiting the sample. Given that only about 6% of individuals work in the construction sector, limiting the sample reduces the precision of the estimates so that we are not able to identify sectoral differences in wage growth for sectors in which few individuals work. Finally, we test whether the results are robust to the identifying assumptions of our preferred specification by estimating the model using fixed effects, a diff-in-diff specification, a dynamic version of equation (4) which includes a control for wages in 2000 and a dynamic model instrumenting for the lagged dependent variable using the income from 1997. When we estimate the model as a fixed effects specification, we assume the following process for wages

$$\ln y_{it} = a + b\, H_{it} + \boldsymbol{X}'_{it}\, \boldsymbol{c} + \boldsymbol{S}'_{it}\, \boldsymbol{d} + \boldsymbol{Z}'_{it}\, \boldsymbol{e} + (f_{pt} + g_i + u_{it}) \tag{9}$$

for $t = 1, 2$ which differs from equation 4 in two respects: first, we replace H_{it} with zero in when $t = 1$; second, we now control for contemporaneous background characteristics $\boldsymbol{X}$, sectors $\boldsymbol{S}$ and categories $\boldsymbol{Z}$ rather than conditioning on lagged characteristics. When estimating the model in a

Table 9: Dependent Variable: Changes in Log of Monthly Wages, Month and Year Recall Combined

	Houses Destroyed	Intensity Measure	Intensity Measure District FE
	(1)	(2)	(3)
Earthquake	0.845 (2.275)	0.068 (0.066)	-.084 (0.172)
Earthquake*Agriculture	8.348 (3.077)***	0.321 (0.079)***	0.302 (0.082)***
Earthquake*Construction	1.027 (3.993)	0.031 (0.081)	0.022 (0.082)
Earthquake*Manufacturing	3.114 (2.629)	-.009 (0.079)	-.011 (0.08)
Earthquake*Social Services	2.633 (3.086)	-.003 (0.064)	0.005 (0.066)
Obs.	2917	2917	2917
R^2	0.052	0.058	0.088

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 10: Dependent Variable: Changes in Log of Monthly Wages, Varying Control Groups

	Intensity Measure MMI>4	Intensity Measure MMI>4.2	Intensity Measure MMI>4.4
	(1)	(2)	(3)
Earthquake	0.084 (0.054)	0.084 (0.059)	0.137* (0.082)
Earthquake*Agriculture	0.274*** (0.068)	0.224*** (0.073)	0.188** (0.092)
Earthquake*Construction	0.053 (0.051)	0.031 (0.054)	-.032 (0.074)
Earthquake*Manufacturing	0.025 (0.066)	0.041 (0.069)	0.034 (0.075)
Earthquake*Social Services	0.052 (0.047)	0.026 (0.05)	-.014 (0.065)
Obs.	2048	1616	1118
R^2	0.089	0.104	0.109

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels. Columns (1)-(3) limit the sample to individuals with an exposure above 3.8, 4.1 and 4.2 on the mercalli scale.

Diff-in-Diff specification, we assume the following process

$$\ln y_{it} = a_t + b\,H_i + D_t + w\,H_i * D_t + \boldsymbol{X}'_{it}\,\boldsymbol{c} + \boldsymbol{S}'_{it}\,\boldsymbol{d} + \boldsymbol{Z}'_{it}\,\boldsymbol{e} + (f_{pt} + u_{it}) \tag{10}$$

for $t = 1,2$ which differs from equation 4 in three respects: first, as we have two equations now to estimate H_i appears twice. The coefficient b captures differences in wages between treatment and control areas; second, we now include a dummy variable D_t that is equal to one in $t = 2$. The coefficient on the interaction term, w therefore indicates the effect of the earthquake on wages.

Table 11: Dependent Variable: Log of Monthly Wages, Fixed Effects

	Houses Destroyed	Houses Destroyed	Intensity Measure	Intensity Measure
	(1)	(2)	(3)	(4)
Earthquake	4.977***	1.677	0.136***	0.003
	(0.875)	(1.101)	(0.051)	(0.026)
Earthquake*Agriculture		10.452***		0.289***
		(3.434)		(0.084)
Earthquake*Construction		3.488*		0.102**
		(1.960)		(0.048)
Earthquake*Manufacturing		1.811		0.003
		(2.392)		(0.05)
Earthquake*Social Services		0.702		0.005
		(1.578)		(0.041)
Obs.	4940	4940	4940	4940
R^2	0.086	0.088	0.083	0.089

Notes: All models control for age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 12: Dependent Variable: Log of Monthly Wages, Diff-in-Diff

	Houses Destroyed	Houses Destroyed	Intensity Measure	Intensity Measure
	(1)	(2)	(3)	(4)
Earthquake	4.718***	1.481	0.069***	0.015
	(0.536)	(1.622)	(0.021)	(0.033)
Earthquake*Agriculture		9.496**		0.296***
		(4.619)		(0.098)
Earthquake*Construction		4.977*		0.13**
		(2.670)		(0.063)
Earthquake*Manufacturing		3.070		0.027
		(2.595)		(0.061)
Earthquake*Social Services		2.827		-.0009
		(2.724)		(0.062)
Obs.	4940	4940	4940	4940
R^2	0.281	0.284	0.278	0.284

Notes: All models control for age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

Third, as in equation (9), we control for contemporaneous characteristics. The differential return to agriculture workers in both, the fixed effects results in table 11 and the diff-in-diff specification in table 12 are very similar to our baseline specification in table 2.

The dynamic model in table 13 yields slightly lower estimates. However, once we instrument for the lagged dependent variable using wages in the previous period in table 14 we see that the results are again very close to our baseline specification in equation (4). We have also estimated the model as a dynamic random effects model and as a dynamic fixed effects IV model using wages in 1997 as instruments and the coefficients and standard errors are virtually identical to the results presented here. As discussed in the previous section, we prefer equation (4) as it conditions on baseline characteristics which are not affected by potentially endogenous movement across sectors.

However, the robustness exercise shows that the results are not due to selecting a particular set of identifying assumptions, but robust across various models[49].

Table 13: Dependent Variable: Changes in Log of Monthly Wages, Dynamic Model

	Houses Destroyed	Houses Destroyed	Intensity Measure	Intensity Measure
	(1)	(2)	(3)	(4)
Earthquake	3.215***	2.415**	0.107***	0.097**
	(0.97)	(1.145)	(0.04)	(0.042)
Earthquake*Agriculture		4.805***		0.187***
		(1.695)		(0.052)
Earthquake*Construction		0.829		0.035
		(1.575)		(0.041)
Earthquake*Manufacturing		0.667		-.040
		(1.631)		(0.043)
Earthquake*Social Services		0.328		0.023
		(1.271)		(0.029)
Obs.	2471	2471	2471	2471
R^2	0.346	0.347	0.345	0.349

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 14: Dependent Variable: Changes in Log of Monthly Wages, Dynamic Model - IV

	Houses Destroyed	Houses Destroyed	Intensity Measure	Intensity Measure
	(1)	(2)	(3)	(4)
Earthquake	3.918***	2.125	0.125***	0.097**
	(1.032)	(1.320)	(0.043)	(0.045)
Earthquake*Agriculture		7.268***		0.269***
		(2.557)		(0.068)
Earthquake*Construction		1.771		0.064
		(1.736)		(0.045)
Earthquake*Manufacturing		2.698		-.003
		(2.153)		(0.052)
Earthquake*Social Services		1.134		0.03
		(1.846)		(0.035)
Obs.	2471	2471	2471	2471
R^2	0.257	0.26	0.255	0.266

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

A further concern is the measurement of wages in the agriculture sector. The household questionnaire records the net profit earned from farm businesses (or the share if the business is owned

[49]We have conducted a range of further robustness checks. First, we have estimated the base results instrumenting with the mercalli measure for the destruction measure, as well as the interaction terms; second, we have re-estimated all equations using the full sample of workers aged between 15 and 85; third, we have applied the attrition adjusted cross sectional individual sampling weights provided by the IFLS which make the 2007 IFLS sample of individuals representative for the 2007 population of individuals living in the original IFLS 13 provinces; our results remain robust.

by multiple individuals); the individual level questionnaire, for which the wage data comes, asks individuals to report their profits at the individual level, but each respondent might also report the full profit. This only biases our results if for some reason the reporting of individual level profits has increased for individuals who were affected by the earthquake. We test whether self-employed agricultural workers are driving these results from several angles: first, we split the sample by work category; second, we drop self-employed agricultural workers. In both cases the significant positive effect of the earthquake on wages in agriculture remains. Finally, we estimate our base model in equation (4) but instead of estimating it at the individual level, we use changes in total household expenditure as the dependent variable, and control for the sector of employment of the household head in 2000[50]. In credit constrained environments, household expenditure and incomes are likely to be similar. Table 15 shows that households in which the household head was employed in the agricultural sector before the earthquake had significantly higher per capita expenditure, supporting that the positive effect on wages found in the wage regressions is not simply an artefact of reporting.

Table 15: Dependent Variable: Changes in Log of Monthly per capita Expenditures

	Houses Destroyed	Houses Destroyed	Intensity Measure	Intensity Measure
	(1)	(2)	(3)	(4)
Earthquake	1.138	0.292	0.042	0.053
	(1.386)	(1.613)	(0.06)	(0.061)
Earthquake*Agriculture		4.991***		0.119***
		(1.647)		(0.041)
Earthquake*Construction		-.680		-.023
		(2.064)		(0.049)
Earthquake*Manufacturing		3.380		-.005
		(2.922)		(0.059)
Earthquake*Social Services		-1.454		-.094**
		(2.067)		(0.046)
Obs.	1787	1787	1787	1787
R^2	0.05	0.058	0.05	0.064

Notes: All models control for baseline age, gender, sector of employment, category of employment of the household head; rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

A.3 Exogeneity of Earthquake

As figure 1 showed, a large area of Indonesia is exposed to substantial risks of earthquakes; the location of the Yogyakarta earthquake is actually in an area that does not fall into the highest deciles of peak ground acceleration values for areas that exhibit a 10% chance of exceeding peak ground acceleration of 2 metres per second in a 50 year period. We control for a large range of baseline characteristics determining wage growth, but we still worry that unobservables which are correlated with the incidence of the earthquake are biasing our results. For example, if the most productive individuals move to areas with minimal earthquake probability, the productivity of individuals affected by the earthquake is lower than in 'safe' areas. Unobserved productivity will then be negatively correlated with the earthquake; if productivity affects wage growth, we would falsely attribute lower

[50]Similar to wages, we convert per capita expenditure to 2007 Rupiah.

wage growth in affected areas to the earthquake.

Table 16: Dependent Variable: Baseline Log of Monthly Wages

	Houses Destroyed	Houses Destroyed	Houses Destroyed IV	Intensity Measure	Intensity Measure	Intensity Measure
	(1)	(2)	(3)	(4)	(5)	(6)
Houses destroyed	-2.028	-1.575*	-1.475			
	(1.597)	(0.889)	(2.683)			
Mercalli				0.027	-.029	-.120
				(0.075)	(0.053)	(0.123)
Controls	Age, Sex	Full Set	Full Set	Age, Sex	Full Set	Full Set
District Fixed Effects	NO	NO	NO	NO	NO	YES
Obs.	2471	2471	2471	2471	2471	2471

Notes: Full controls include baseline age, age squared, gender, education, sector of employment, category of employment, rural/urban location, month of the 2000 survey and province specific trends; all models include province fixed effects; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

To test for this, we conduct a placebo experiment in which we test whether baseline wages are different before the earthquake. For this, we merge the earthquake exposure measures to individuals' baseline district and communities. Table 16 shows the correlates of baseline wages in 2000 for our two main measures for the earthquake shock: district level destruction and the mercalli measure of earthquake intensity. District level destruction measures the number of houses destroyed per person using the population in 2005. The highest level of destruction is in the district of Bantul, where 78,622 houses were destroyed and the population in 2005 was 839,536, so that 0.09 houses were destroyed per person. The mercalli measure ranges from a maximum exposure of 8 to a value of 3.8 for the households furthest away in the sample. Columns (1) and (4) control for age, age squared and the gender of the individual, and the remaining columns include the full set of baseline controls. For the district level destruction measure, we find a small and marginally significant negative effect of the placebo shock, suggesting that baseline wages were 1.5% lower when a district had a one percentage point higher destruction; however, the destruction measure is endogenous. If wages proxy for the level of development, and housing construction was of poorer quality in these areas, then we would expect subsequent destruction to be higher. In column (3), we instrument for the destruction measure using the mercalli measure[51]. We no longer find any significant effect anymore. When using our exogenous measure of the effect of the earthquake, the mercalli intensity scale, we do not find any significant differences in the wages of individuals affected by the earthquake. As there is district level variation in the mercalli intensity measure through linking communities' GPS coordinates with the pixels of instrumental intensity of the earthquake, we can add district dummy variables to account for differences in district level wage growth rates in column (6). Again, we do not observe any significant differences.

As the main specification considers the effect of the earthquake on wage growth, it is important to test whether wage growth was similar in treatment and control areas before the earthquake. For individuals for which we have positive wages in 1997, we have estimated the same equation using wage growth between 1997 and 2000; table 17 shows the result of the same equations estimated

[51]The Kleibergen-Paap Wald rk F statistic is 36.01, so that we can reject the null that the model is weakly identified.

above with log wages, but now for wage growth. The table illustrates that we do not find any significant differences in the level of wage growth for both earthquake measures which would violate the common trends assumption.

Table 17: Dependent Variable: Growth of Log Wages 1997-2000

	Houses Destroyed	Houses Destroyed	Houses Destroyed IV	Intensity Measure	Intensity Measure	Intensity Measure
	(1)	(2)	(3)	(4)	(5)	(6)
Houses destroyed	0.617	0.67	1.710			
	(0.984)	(0.965)	(2.900)			
Mercalli				-.018	0.096	0.096
				(0.054)	(0.143)	(0.143)
Controls	Age, Sex	Full Set	Full Set	Age, Sex	Full Set	Full Set
District Fixed Effects	NO	NO	NO	NO	NO	YES
Obs.	1499	1499	1499	1499	1499	1499

Notes: Full controls include baseline age, age squared, gender, education, sector of employment, category of employment, rural/urban location, month of the 2000 survey and province specific trends; all models include province fixed effects; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

A.4 Selection into Labour Market

We only include individuals in our sample for which we have positive wages in both periods. A concern is that the earthquake causes endogenous selection into the labour market, or into recording non-zero wages. Suppose that individuals differ along their unobservable endowment of creative adaptiveness, so how quickly they adapt to a new situation and develop new solutions, and there are high-endowment and low-endowment individuals. Low-endowment individuals are then going to be more likely to drop out of the labour market after the earthquake, whereas high-endowment individuals are more likely to keep their jobs. But if high endowment individuals were more likely to enjoy higher wages independent of the earthquake, the effect of the earthquake would be biased upwards because we are missing these low-endowment individuals. We therefore examine whether unobservable determinants of wages of individuals who earned a positive wage in 2000 but are not in our wage-earning sample in 2007 are correlated with the earthquake. We would like to estimate the following model

$$\ln H_i = \zeta_0 + \zeta_1 \varepsilon_{i1} + \zeta_2 D_{\Delta i} + \zeta_3 \varepsilon_{i1} D_{\Delta i} + v_{i2} \tag{11}$$

where H_i denotes exposure to the earthquake, ε_{i1} are unobservables, and $D_{\Delta i}$ is a dummy variable that is equal to one if a worker had a positive wage in 2000 but not in 2007. The coefficient ζ_3 would the tell us whether unobservables of workers who record positive wages in 2000 but not in 2007 are correlated with earthquake exposure. To do this, we can get an estimate of ε_{i1} from assuming that

$$\ln y_{i1} = \kappa_0 + \kappa_1 X_{i1} + \varepsilon_{i1} \tag{12}$$

where y_{i1} are baseline wages and X_{i1} are baseline characteristics[52], κ_0 is a constant and ε_{i1} is the error term. Plugging (12) into (11) we get

$$\begin{aligned}\ln H_{i2} =&\zeta_0 + \zeta_1 \left[\ln y_{i1} - \kappa_0 + \kappa_1 X_{i1}\right] + \zeta_2 D_{\Delta i} \\ &+ \zeta_3 \left[\ln y_{i1} - \kappa_0 + \kappa_1 X_{i1}\right] D_{\Delta i} + v_{i2} \qquad (13) \\ =&(\zeta_0 - \zeta_1 \kappa_0) + \zeta_1 \, ln y_{i1} + \zeta_1 \kappa_1 X_{i1} + (\zeta_2 - \zeta_3 \kappa_0) D_{\Delta i} \\ &+ \zeta_3 \, ln y_{i1} D_{\Delta i} - \zeta_3 \kappa_1 X_{i1} D_{\Delta i} + v_{i2} \qquad (14)\end{aligned}$$

which we can estimate. The intuition is that once we include all our baseline controls, the variable $\ln y_{i1}$ should only include unobservable determinants of wages, so that it proxies for residual wages. We can then test whether these unobservables are different for individuals who reported a positive wage in 2000 but not in 2007.

Table 18: Dependent Variable: Earthquake

	Houses Destroyed	Houses Destroyed	Intensity Measure	Intensity Measure	Intensity Measure
	(1)	(2)	(3)	(4)	(5)
ζ_1	-.0005	-.0005*	0.004	-.006	-.002
	(0.0004)	(0.0003)	(0.011)	(0.009)	(0.002)
$(\zeta_2 - \zeta_3 \kappa_0)$	-.0003	0.006	-.282	-.267	-.002
	(0.01)	(0.011)	(0.272)	(0.281)	(0.067)
ζ_3	0.0002	-.0002	0.0005	0.015	0.003
	(0.0004)	(0.0004)	(0.013)	(0.012)	(0.003)
Controls	Age, Sex	Full Set	Age, Sex	Full Set	Full Set
District Fixed Effects	NO	NO	NO	NO	YES
Obs.	3216	3216	3216	3216	3216

Notes: Full controls include baseline age, age squared, gender, education, sector of employment, category of employment, rural/urban location, month of the 2000 survey and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

There are 745 individuals in our sample who reported a positive wage in 2000 but not in 2007. Although this seems high, it is not out of line with what we observe in the whole sample. When looking at the whole sample for 2000-2007, out of those individuals aged below 55 in 2007 who recorded a positive wage in 2000, 23.4% did not record a positive wage in 2007. When we exclude the individuals who were affected by the earthquake this number is higher (24.7%) rather than lower, suggesting that it is not the earthquake leading to these high transition probabilities; it rather appears to be a feature of the labour market. Table 18 shows the correlation between the residual of the wage equation and earthquake intensity; columns (1) and (3) control for age, age squared and sex, while the remaining columns include the full set of controls. Column (5) adds district fixed effects. The third row shows that the interaction effect between baseline residual wages and the dummy for not reporting wages in 2007 is insignificant. In other words, individuals who reported positive wages in 2000 but did not report positive wages in 2007 did not have unobservable determinants of wages which are systematically correlated with the earthquake[53]. The control for baseline

[52]For simplicity of exposition, assume this is a scalar variable, for example, years of schooling.

[53]We have estimated the model in column (5) including interaction effects with the baseline sector of employment

wages is significant and negative in column (2), but the coefficient is very small and the effect is not there when we use the exogenous mercalli earthquake measure as the dependent variable.

A.5 Attrition and Migration

Attrition is a significant concern when analysing longitudinal data sets, and particularly so in developing countries. Indeed, Thomas et al. (2012) show that households which were not interviewed in 2007 tended to have higher education, more highly educated parents and come from households with higher consumption at baseline in 1993. They further find that per capita expenditure of longer distance movers between 1993 and 1997 which were tracked was 75% higher compared to non-movers.

If the survey misses individuals with the steepest wage growth, we would underestimate the average growth in wages by leaving out mover households. Attrition and migration are important when considering the effect of natural disasters. When individuals in 2007 were asked in the migration section of the individual questionnaire, the three most frequently stated reasons for migration were work-related migration (34%), marriage (15%) and education (11%); only 0.33% of individuals give natural disasters as a reason for migration. Both Halliday (2006) and Yang (2008) find that two earthquakes in El Salvador reduced the probability that households send a migrant, due to either liquidity constraints or a higher need for family labour at home.

It is therefore important to test for differential migration and attrition depending on the proximity of household to the earthquake. We construct a variable that is equal to one if a household in our sample in 2000 moved from an earthquake affected district to a district not affected by the earthquake and zero otherwise[54]. In a linear probability model, we regress this measure on baseline wages and add controls in column (2), and column (3) includes district fixed effects. Similar to the test for selection, we can interpret the coefficient on the wage variable as a proxy for unobservable wages. Table 19 shows that individuals who moved outside the earthquake affected areas did not have significantly different unobservables determining baseline wages, so that that migration out of earthquake affected areas is not correlated with higher or lower unobservables.

Out of the all individuals for which we have positive wages in 2000, only 3% were living in households which were not found for the follow up interview in 2007, so that attrition is low for this sample. We tested whether attrition is more likely in earthquake affected areas, as well as whether it is more likely for individuals with lower baseline wages, and did not find any evidence for any systematic attrition related to the earthquake[55]. Therefore, there does not seem to be evidence that the earthquake led to higher migration or attrition of individuals at a specific location of the wage distribution, thereby biasing the results[56].

and category of employment; we do not that find individuals who reported positive wages in 2000 but not in 2007 who were working in a specific sector had unobservable determinants of wages which are systematically correlated with the earthquake.

[54]We define districts affected by the earthquake as those which had any houses destroyed.

[55]Frankenberg et al. (2005), using the IFLS data, do not find evidence that forest fires led to differential attrition.

[56]We have also used the complete sample of all IFLS households who lived in the control and treatment areas in 2000

Table 19: Dependent Variable: Whether Household Moved Away from Earthquake Affected District

	Any Destruction	Any Destruction	Any Destruction
	(1)	(2)	(3)
$\ln y_{2000}$	-.0009	-.002	-.002
	(0.002)	(0.003)	(0.002)
Controls	Age, Sex	Full Set	Full Set
District Fixed Effects	NO	NO	YES
Obs.	3216	3216	3216

Notes: Full controls include baseline age, age squared, gender, education, sector of employment, category of employment, rural/urban location, month of the 2000 survey and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

A.6 Robustness of Mechanism

This section presents robustness tests for the finding presented in 5.2.3, by taking cut-offs in the ratio of consumption over production between 1 and 3 with 0.2 steps. Figure 4 and 5 in the appendix show the range of values of the coefficients on $\pi_1 + \pi_5$, $\pi_1 + \pi_6$ and $\pi_1 + \pi_7$ for both the destruction as well as the mercalli earthquake measure. Consistent with the expectation, the change in prices is significantly higher for communities which shifted to being net buyers in the sample period. The results are slightly cleaner when using the mercalli measure, most likely due to the finer measure when comparing across communities, since the destruction measure only varies at the district level, assigning the same value to all communities in the same district. What emerges, nevertheless, is that communities which became net buyers in this period experienced the highest growth in rice prices when focusing on the coefficients with p-values of 0.1 or less. The fact that we do not observe consistent evidence for decreases in the price for net seller communities and increases in the price for net buyer communities suggests that trade continued in the aftermath of the earthquake[57].

A.7 Data Sources to examine Heterogeneity with respect to Distance to Markets and Ports

To measure proximity to cities we use data from the Atlas of Urban Expansion on the Universe of 3,636 cities, out of which 77 are in Indonesia[58]. As alternative source we use data on 7,343 populated places (out of which 105 are in Indonesia) which are derived from LandScan maps[59]. For ports we use the World Port Index provided by the National Geospatial Intelligence Agency which

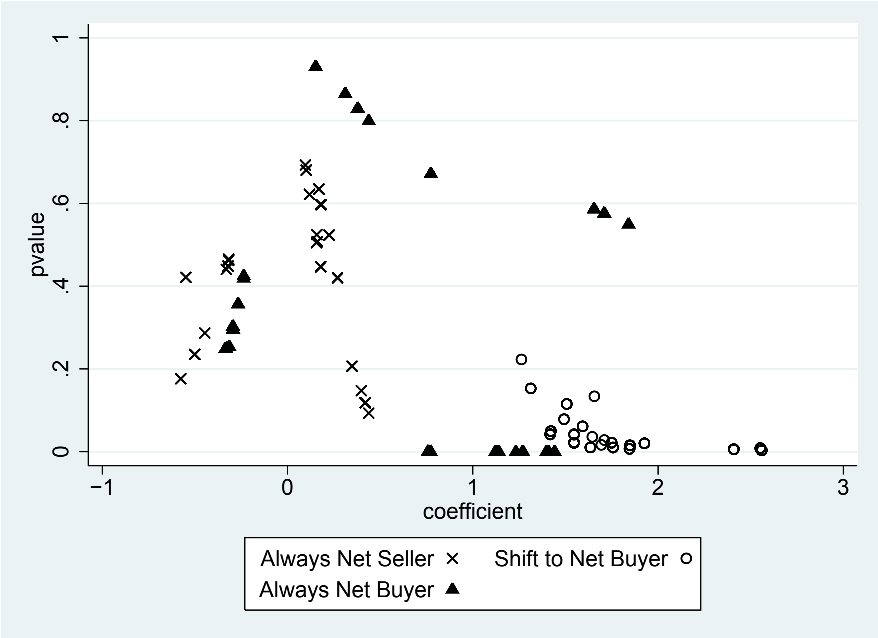
and merged them with their follow up households in the 2007 round. We then constructed an indicator whether a household interviewed in 2000 in the control and treatment areas was not found in 2007, and regressed the indicator on the earthquake measures. We did not find any relationship between exposure to the shock and subsequent probability of being in the sample, and there is no evidence that poorer households affected by the earthquake are less likely to be tracked in the survey in 2007. This suggests that there is no evidence that the earthquake led to differential patterns of attrition for lower and higher income families.

[57]We have also estimated the results controlling for the month of the first interview in a community as well as the minimum number of days at the level of the community between the earthquake and the first interview and the results are substantively the same.

[58]See http://www.lincolninst.edu/subcenters/atlas-urban-expansion/google-earth-data.aspx for further information.

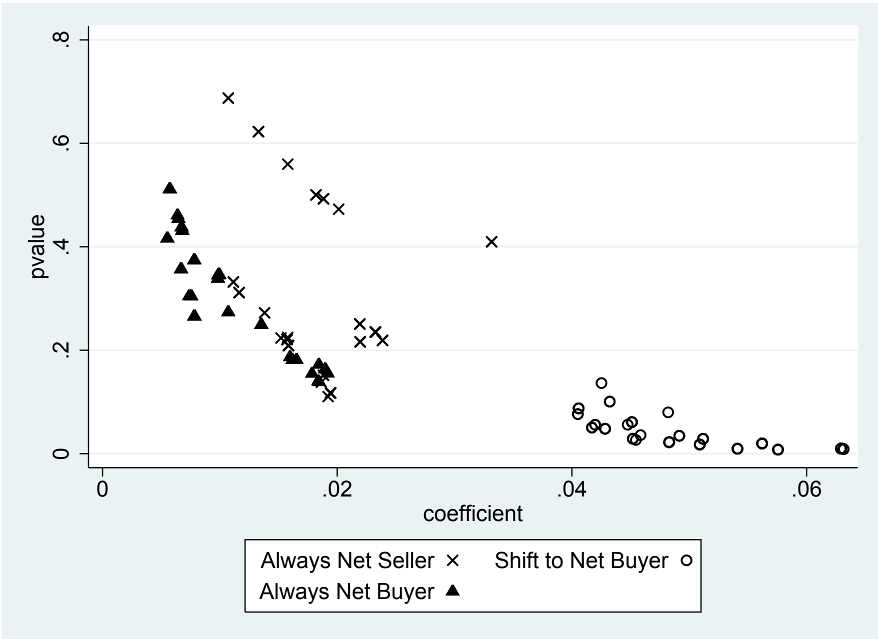
[59]See http://www.naturalearthdata.com/downloads/10m-cultural-vectors/10m-populated-places/ for further information.

Figure 4: Range of Coefficients with Varying Cut-offs (Destruction Measure)



Notes: Circles represent the coefficient for communities which shifted to net buyers ($\pi_1 + \pi_5$); triangles represent the coefficient for communities which were net buyers in both periods ($\pi_1 + \pi_6$); crosses represent the coefficient for communities which were always net sellers ($\pi_1 + \pi_7$); communities which shifted to net sellers are the omitted category; standard errors clustered at the district level.

Figure 5: Range of Coefficients with Varying Cut-offs (Mercalli Measure)



Notes: Circles represent the coefficient for communities which shifted to net buyers ($\pi_1 + \pi_5$); triangles represent the coefficient for communities which were net buyers in both periods ($\pi_1 + \pi_6$); crosses represent the coefficient for communities which were always net sellers ($\pi_1 + \pi_7$); communities which shifted to net sellers are the omitted category; standard errors clustered at the district level.

contains data on 3,687 ports worldwide (123 in Indonesia) [60].

[60] See `http://msi.nga.mil/NGAPortal/MSI.portal?_nfpb=true&_pageLabel=msi_portal_page_62&pubCode=0015` for further information.

B Additional Tables

Table 20: Median of Wages and Wage Growth by Employment Category

	N	Hourly†	Monthly	Hourly†	Monthly
		Levels in 2000		Growth by Category in 2000	
	(1)	(2)	(3)	(4)	(5)
Self-employed	996	2035.1	368,952.9	5.1%	7.5%
Firm Owner	44	6401.7	1,295,379.0	-5.9%	7.2%
Government worker	219	8115.1	1,286,428.0	32.2%	33.9%
Private Worker	1212	2219.0	454,797.8	26.8%	22.7%
Total	2471	2357.9	464,079.4	21.4%	19.9%

	N	Hourly†	Monthly	Hourly†	Monthly
		Levels 2007		Growth by Category in 2007	
	(1)	(2)	(3)	(4)	(5)
Self-employed	1332	2199.5	400,000.0	6.5%	4.5%
Firm Owner	71	5278.8	1,000,000.0	5.9%	8.1%
Government worker	237	10997.5	1,700,000.0	36.7%	37.4%
Private Worker	831	3079.3	600,000.0	31.6%	26.8%
Total	2471	2886.8	500,000.0	21.4%	19.9%

Notes: †hourly wages in 2007 missing for 2 individuals; employment categories are defined as follows: Self-employed includes self-employed with unpaid family worker/temporary worker, casual worker in agriculture, casual worker not in agriculture; firm owners are self-employed with permanent worker. Columns (4) and (5) show wage growth, where the top panel shows wage growth for workers employed in a particular category in 2000, and the bottom panel shows wage growth for workers employed in a particular category in 2007. All figures are in 2007 Indonesian Rupiah using the CPI for 43 cities in Indonesia.

Table 21: Median Wages and Wage Growth by Employment Sector

	Levels in 2000			Growth by Category in 2000	
	N	Hourly†	Monthly	Hourly†	Monthly
	(1)	(2)	(3)	(4)	(5)
Agriculture	444	1840.0	368,952.9	7.1%	7.5%
Construction	217	2485.2	553,429.3	22.4%	19.9%
Manufacturing	502	2143.6	421,949.2	18.7%	13.7%
Commercial Services	747	2143.6	417,671.4	19.9%	13.2%
Social Services	561	4019.2	649,711.1	27.5%	30.0%
Total	2471	2357.9	464,079.4	21.4%	19.9%

	Levels 2007			Growth by category in 2007	
	N	Hourly†	Monthly	Hourly†	Monthly
	(1)	(2)	(3)	(4)	(5)
Agriculture	476	1924.6	300,000.0	1.4%	-3.2%
Construction	186	3150.3	600,000.0	13.4%	19.9%
Manufacturing	443	2969.3	600,000.0	27.7%	23.5%
Commercial Services	794	2474.4	500,000.0	18.4%	12.2%
Social Services	572	4925.3	845,000.0	29.7%	29.8%
Total	2471	2886.8	500,000.0	21.4%	19.9%

Notes: †hourly wages in 2007 missing for 2 individuals; employment sectors are defined as follows: agriculture includes forestry fishing and hunting; construction electricity, gas and water and mining; commercial services comprises wholesale, retail, restaurants, hotels, transportation, storage communications, finance, insurance, real estate and business services. Columns (4) and (5) show wage growth, where the top panel shows wage growth for workers employed in a particular sector in 2000, and the bottom panel shows wage growth for workers employed in a particular sector in 2007. All figures are in 2007 Indonesian Rupiah using the CPI for 43 cities in Indonesia.

Table 22: Housing Destruction per District

District	Houses Destroyed	Houses Damaged	Mercalli	Av.mercalli	Population 2005
	(1)	(2)	(3)	(4)	(5)
Bantul	78,622	69,818	7.6	7.7	871,203
Klaten	32,277	63,615	5.8	6.3	1,119,812
Sleman	6,186	16,065	6.6	6.8	999,586
Kota Yogyakarta	4,129	10,219	7.8	7.7	439,393
Kulon Progo	4,009	5,134	6.2	5.9	373,770
Gunung Kidul	2,957	5,783	6.2	6.4	681,554
Sukoharjo	644	885	5.6	5.6	805,096
Magelang	386	386	5.2	5.2	1,141,503
Karanganyar	66	75	4.8	5.0	791,177
Purworejo	29	347	5.2	5.4	713,149
Temanggung	24	61	4.8	4.9	686,851
Kebumen	3	0	4.8	5.0	1,193,854

Notes: Desinventar database and USGS modified mercalli intensity scale. Column (4) lists the average modified mercalli intensity scale per district. Column (5) shows the average modified mercalli intensity scale of the sample, replacing the data in column (4) with exact shaking values for individuals in the original IFLS communities.

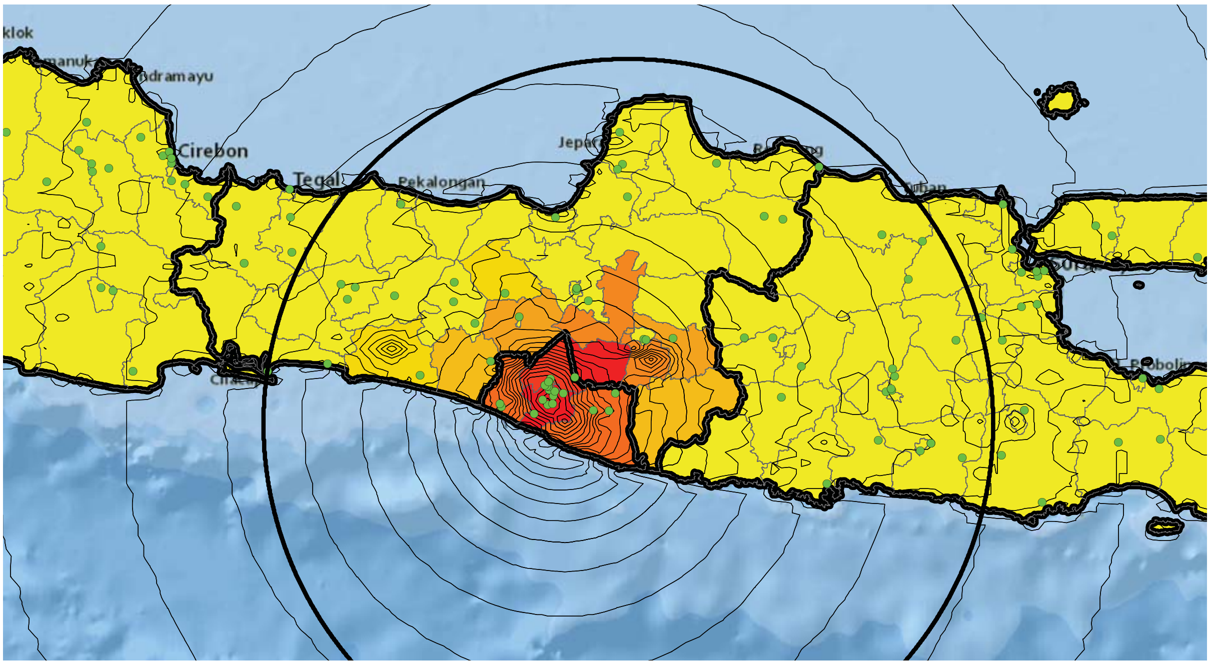
Table 23: Dependent Variable: Changes in Log of Monthly Wages

	ratio	log	mercalli
	(1)	(2)	(3)
Houses dest/population	4.467***		
	(1.111)		
Log Housesdestroyed		0.053***	
		(0.014)	
Mercalli			0.14***
			(0.051)
Agriculture	-.143	-.136	-.139
	(0.104)	(0.105)	(0.104)
Construction	-.226**	-.216**	-.226**
	(0.088)	(0.088)	(0.089)
Manufacturing	-.226***	-.225***	-.226***
	(0.059)	(0.059)	(0.059)
Social Services	0.015	0.009	0.006
	(0.069)	(0.07)	(0.07)
Primary	-.095	-.092	-.107
	(0.113)	(0.111)	(0.112)
Secondary	-.089	-.100	-.113
	(0.123)	(0.121)	(0.122)
Tertiary	-.058	-.068	-.079
	(0.138)	(0.135)	(0.135)
Age	0.012	0.012	0.013
	(0.02)	(0.021)	(0.021)
Age Squared	-.0003	-.0003	-.0003
	(0.0003)	(0.0003)	(0.0003)
Urban	0.129*	0.17***	0.152***
	(0.075)	(0.045)	(0.046)
Male	-.130***	-.133***	-.127***
	(0.046)	(0.046)	(0.046)
Firm Owner	0.065	0.066	0.071
	(0.151)	(0.152)	(0.151)
Wage Worker	0.216**	0.214**	0.22**
	(0.097)	(0.098)	(0.098)
Government Worker	0.145**	0.143**	0.146**
	(0.06)	(0.061)	(0.061)
Central Java	0.084	0.341**	0.226
	(0.087)	(0.148)	(0.148)
East Java	0.222**	0.518***	0.443**
	(0.088)	(0.16)	(0.176)
West Java	0.107	0.402**	0.356*
	(0.099)	(0.165)	(0.186)
Hours Worked	-.005***	-.005***	-.005***
	(0.001)	(0.001)	(0.001)
Days since EQ	-.0004	-.0002	-.0003
	(0.003)	(0.003)	(0.003)
Const.	0.142	-.291	-.732
	(1.766)	(1.780)	(1.799)
Obs.	2471	2471	2471
R^2	0.071	0.07	0.069

Notes: All models control for month of each survey round; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

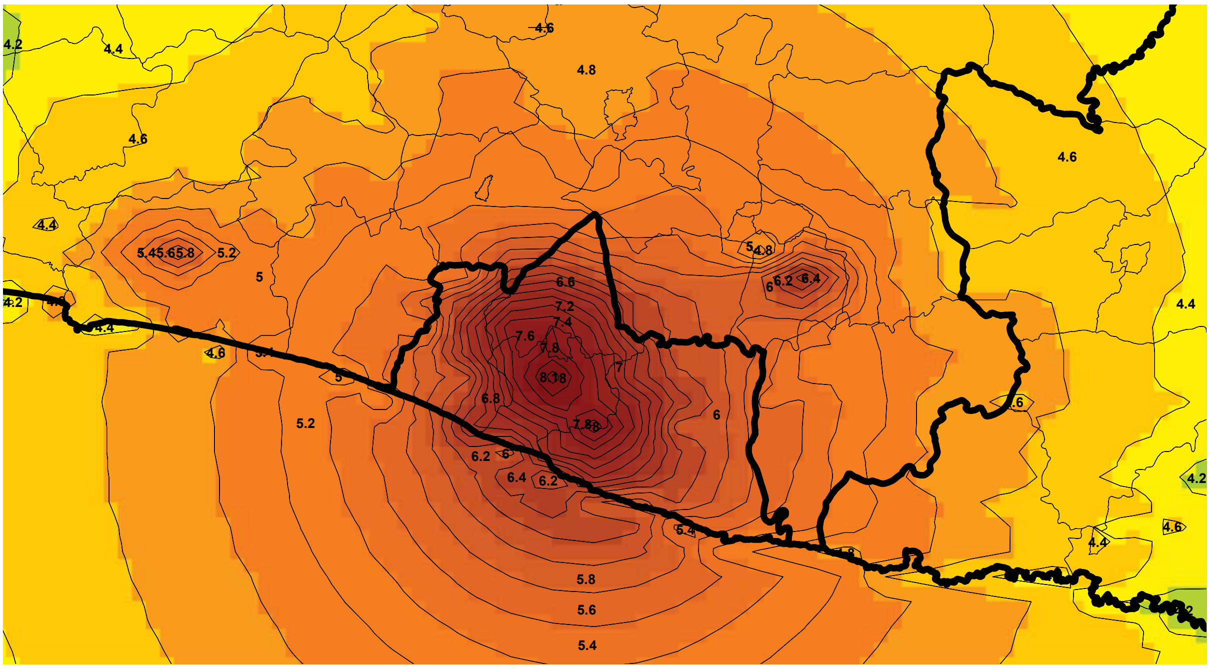
C Additional Figures

Figure 6: Yogyakarta Earthquake, 27 May 2006 at 05:53:58 AM



Source: ArcGIS 10; data from US Geological Survey and IFLS communities.

Figure 7: Modified Mercalli Intensity Map zoomed into the Epicentre



Source: ArcGIS 10; data from US Geological Survey.