Thesis

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Title: Estimating the Real Price of a Natural Disaster: An Analysis of Women Labour Force Participation After a Disaster.
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Abstract
Men and women are unequal hit by the effects of a natural disaster. Women are worse-off and more women die in the aftermath of a natural disaster. This paper explores if women are also worse off in their career opportunities. It is important to know if a natural disaster deteriorates equity between men and women, so that recovery policy can be adjusted accordingly. This paper distinguishes between the effect of various disaster types and tests the effect of a natural disaster on ten different employment sectors. Data on individuals is retrieved from the Indonesian Family Life Survey and data on natural disaster is retrieved from EM-DAT. The data on natural disasters covers 26 disasters between 1994 and 2014. The data on individuals are from three surveys in 2000, 2007 and 2014. This research uses a dummy for paid work as a dependent variable and a dummy for whether a natural disaster occurred in the region of the participant or not. Using fixed effects for year, kecamatan, and household this paper found no significant effect of natural disasters on labour participation among men and women. The results are rather unlikely; therefore, this paper suspects a type II error. For future research a larger dataset and a more flexible cut-off point to determine the severity of a natural disaster is needed.

Contents

Introduction

Currently the world is facing an increasing number of natural disasters due to human-caused climate change (Meserve, 2008; Ostrom 2009; Banholzer, Kossin and Donner, 2014; Edenhofer, 2014). Countries suffer increasingly from rising sea levels, extreme droughts, heavy rainfalls, reduced food supplies, and other natural disasters (Meserve, 2008; Ostrom, 2009). New institutions and organization have been established to help in the mitigation and adaptation of climate change (IPCC, 2021; GCA, 2021)[1]. Both institutions warn against the increasing amount and the increasing severity of natural disasters that are driven by human-caused climate change (IPCC, 2021; GCA, 2021). The past three decades countries tried to take collective actions to mitigate human-caused global warming in the future. The Kyoto Protocol, the Paris agreement, the European green deal and more recently the Glasgow conference are important examples (Ostrom, 2009; Rogelj et al, 2016; European Union, 2019; Depledge et al, 2022). However, despite mitigation programs it is unavoidable that between 2030 and 2050 the global warming is at least 1.5 Celsius degrees (Masson-Delmotte et al, 2018). Therefore, it is important to get a better understanding of the consequences of a natural disaster.

The literature is clear about the unequal negative impact of a natural disaster on women. (Neumayer and Plumper., 2007; Alam and Rahman., 2014; Pakistan., 2016; Sen., 2012) Neumayer and Plümper (2007) found that even though a natural disaster does not discriminate, more women are killed in the aftermath of a natural disaster than men. Alam and Rahman (2014) reveal that women often encounter reproductive and sexual health problems, as well as increasing domestic violence. Pakistan (2016) explains that vulnerable groups, including women, are more prone due to limited access to resources, reduced physical strength, and weaker social economic status. Sen (2012) states that women population fall short compared to men due to unequal access to survival related goods. However, there is a literature gap on the influence of a natural disaster on women labour force participation.

Determinants of women labour force participation are largely covered in the literature (Goldin, 1994; Duflo, 2012; Schaner and Das, 2016). Schaner and Das (2016) explain how gender norms and role behavior influences supply and demand for labour among women. Goldin (1994) subsequently explains how the substitution effect and the income effect affect women labour supply. Duflo (2012) stresses out the importance of women labour force participation. First, it

[1] The Intergovernmental Panel on Climate Change was founded in 1988 and the Global Center of Adaptation was founded in 2018

is simply equity that women are offered the same chances as men (Duflo, 2012). Second, it increases opportunity for women, and it decreases inequality between men and women (Duflo 2012). Duflo (2012) argues that women labour force participation is strongly related to the legal rights of women as well as their bargaining position in the household. Third, it decreases poverty since paid work increases the money of the entire household and therefore improves the conditions for everyone in the household (Duflo 2012). Altogether, the following research question is formulated:

To what extent are natural disasters influencing women labour force participation in Indonesia?

This paper uses Indonesia to investigate the effect natural disasters have on women labour force participation. Indonesia is chosen due to multiple factors. First, Indonesia is a natural disaster-prone country (Kusumastuti et al, 2014). The country is located between three earth faults, which results in various natural disasters including earthquakes, volcanic eruptions and tsunamis (Kusumastuti et al, 2014; Pambudi, 2018). Indonesia is therefore particularly suitable to research the difference between natural disasters that are influenced by climate change and natural disasters that are not. Second, the country's policy aims to decrease the gap in men and women labour force participation by 25 percent in 2025 (OECD, 2019). Third, Indonesia is a developing country, which underlines the importance of economic development (world bank, 2022).

Next to labour participation in general, this paper also distinguishes between labour sector and disaster type. Additionally, the impact of disaster that occurring longer ago is tested. Information on individuals is coming from the Indonesian Family life Survey (Strauss, Witoelar, and Sikoki, 2016; Strauss et al., 2009; Strauss et al., 2004). This survey includes information on gender, work status, residence, age, married status, etc. For data on natural disasters this paper uses EM-DAT, which covers natural disasters all over the world and distinguishes between country and the kind of natural disaster (Guha-Sapir, Below and Hoyois, n.d.). This paper also controls for GDP, minimum wage, and population on a province level. This data is retrieved from Badan Pusat Statistik.

The contents of this paper are structured as follows. In chapter 2 the existing literature is reviewed, and the justification of the stated hypotheses are given. Chapter 3 shows the data that is used to test the hypotheses, as well as it shows the summary of the statistics. Chapter 4 describes the methods and formula used to estimate the results. Chapter 5 includes the results

of this paper and explains what they entail. Chapter 6 contains a discussion including the limitations and suggestions for future research. At the end of the paper an appendix is found.

Literature review

Determinants of women labour supply and demand

Schaner and Das (2016) explain several determinants of women labour supply and demand. Labour supply is determined by the opportunity cost of work, other household income and social cost. The opportunity cost of working is that there is less time for housework, raising children, and leisure. Other household income is also a determinant of labour supply, because for a low household income every additional earning has a larger marginal utility. This leads to an extra incentive for women to work. The last determinant according to Schaner and Das (2016) is that social stigma and norms influence labour supply. If it is inappropriate for women to do certain activities, they are less likely to apply.

Labour demand on the other side is influenced by discrimination and wage gap (Schaner and Das, 2016). The wage gap gives a comparative advantage to women; however, this might be offset by the gender-based discrimination. Another determinant is work environment; the job should be flexible enough to still fulfil obligations at home. Next to that the workplace needs to be safe enough, so that there is no harassment or discrimination. Schaner and Das (2016) argue that some determinants of women labour force participation are multidirectional. For example, are mothers less likely to work because they have to care for a child or are mothers less likely to get a job because they have children?

Inequality during a disaster

Neumayer and Plumper (2007) describe three causes why women are more vulnerable in mortality than men after a disaster hit. First, biological, and physiological difference between men and women (Neumayer and Plumper, 2007). Biologically women are at an advantage since women are less prone to die from diseases and can better cope with food shortages (Neumayer and Plumper, 2007). As a result, the expectation is that women are relatively in a physical advantage compared to men to participate in paid work after a disaster. However, consumption is not equally divided within a family during times of crises. Women often opt out for the benefits of other people within the household, or their consumption is reduced due to social norms. Despite this physiological advantage women are still put into a worse position to rescue themselves (Neumayer and Plumper, 2007). Social norms and role behaviors results in many cultures that women are expected to look after children and elderly, which again reduces their opportunities to rescue themselves (Neumayer and Plumper, 2007). Lastly, women are more

likely to die after a disaster happened through discrimination in resources and due to the lack of law enforcement (Neumayer and Plumper, 2007). Government officials may not be able to (or not willing to) enforce rule of law after there has been a natural disaster. Which in turn results in an increase in criminal activity (Neumayer and Plumper, 2007). The abuse of vulnerable women in the aftermath of a major disaster deteriorates their employment and education decisions (Enarson and Fordham, 2001). Women are often victim of forced marriages and forced into sex work (Enarson and Fordham, 2001). In cultures with forms of gender discrimination, men are more likely to be treated with crucial rescue efforts than women (Neumayer and Plumper, 2007). Enarson and Fordham (2001) state that not sex or gender cuts short women life, but socially constructed roles. Due to social norms, role behaviors, discrimination and the abuse of vulnerable women, the physiological advantage of women can result into a disadvantage to work after a disaster hit.

Substitution and Income Effect

According to Popp (2006) four key macroeconomic variables receive a negative shock due to a natural disaster. Namely, natural resources, physical capital accumulation, human capital accumulation, and technology. The decrease of these macroeconomic variables lowers the real wage. A decrease in the real wage can have two effects, namely a substitution effect or an income effect (Slutsky, 1915; Hicks and Allen, 1934). Goldin (1994) explains how these two effects affect women labour force participation. When income is extremely low, women need to work for subsistence of the family. This is especially obvious in poor agricultural families, where women work on the land to gather food. When income rises, work mainly done by women is bought by the family. For example, food is bought instead of produced by the family itself. This explains the income effect. The substitution effect describes that a rise in income increases the marginal return to labour, consequently the opportunity cost of not working is getting larger. Therefore, more women are expected to participate in the labour force. Skoufias (2003) states on a household level that natural disaster decreases the capital and physical stock of a certain household. In this case the substitution effect explains that a decrease in the real wage decreases women labour force participation. The income effect states that a decrease in the real wage increases women labour force participation.

Natural disaster triggered labour market shifts.

According to Kirchberger (2017) a natural disaster hits the housing sector the hardest, consequently most emergency aid is destined for reconstruction. Therefore, there is a huge demand in the non-tradeable sector, which increases the wage and subsequently the labour

supply. Kirchberger (2017) argues that labour supply is mainly drawn from the low-wage part of the agricultural sector. However, due the decrease in labour supply in the agricultural sector, wages rise in the agricultural sector. Klomp and Hoogezand (2018) nuance this effect because the agricultural sector is often met with trade controls that favor domestic farmers after a disaster hit. Next to that the effect of remittances after a major disaster hit also expects to offset the negative shock on the agricultural sector (Kapri and Ghimire, 2020). On top of that Kirchberger (2017) found that self-employed people had a slightly higher chance of being employed after an earthquake. Nevertheless, Kirchberger (2017) notes that mobility in the agricultural sector is limited since many farms are family farms and the land itself is immobile. Belasen and Polacheck (2008) tested the effect a hurricane in Florida had on the different sectors within the labour markets. They found that the construction and service sector are positively shocked and the manufacturing; trade, transportation, and utility; and finance, investment, and real estate are shocked negatively. Belasen and Polacheck (2009) found that during other hurricanes in Florida the construction sector is also positively affected in the short run. However, as time passes this effect disappears because even the damage of the most destructive hurricane is repaired within two years (Belasen and Polacheck, 2009). Keerthiratne and Tol (2018) state that people on a monthly wage are not affected, while small business owners are. Therefore, more construction work available due to the natural disaster may be beneficial for low skilled workers. Leading to sectorial shift towards construction for low skilled workers (Keerthiratne and Tol, 2018). According to Schaner and Das (2016) Indonesian women are relatively better represented in agriculture than they are represented in construction work. Another disaster triggered labour market shift is that women are moving towards the wholesale, retail, restaurants and hotel sector. With wholesale as an exception, these businesses can be run from home. According to Duflo (2012) running a shop from home gives the opportunity to look after the elderly and children at the same time as running a shop. According to Neumayer and Plumper (2007) the direct increase in pressure to look after elderly and children after a disaster occurred, shifts women to work more in the wholesale, retail, restaurants, and hotels. Duflo (2012) also argues that women may be less committed to their career, or their husbands may be less committed to letting them, which strengthen the ease to switch to running a shop from home.

Disaster types

This paper distinguishes between several disaster types to show whether a climate change triggered natural disaster has a different impact, than a natural disaster that is not driven by

climate change. Klomp (2014) distinguishes different kind of disasters due to their different characteristics. Floods are predictable and only take place in certain times of the year. Floods can take up to three months and precautionary measures can be taken in the forms of building dikes. Wildfires are also more predictable since they also only take place at certain times of the year. However, for wildfires it is harder to take precautionary measures. Volcanic eruptions and earthquakes are not bound to weather conditions as well as they have a more local character compared to floods and wildfires. Another notable difference is that earthquakes only last a few minutes (Klomp 2014). Kirchberger (2017) states that earthquakes stand out in their devastating impact on infrastructure, including houses. Azad, Hossain, and Nasreen (2013) found that poor women are more vulnerable in floods than men, because their usual roles are affected more than the usual roles of men. For example, it is harder to secure food, have clean water, or find adequate shelter. Which affects women more due to social norms and gender roles. Next to that Chowdhury, Parida and Agarwal (2022) found that a flood has a more devastating effect on the agricultural sector. Subsequently labor transfers from agriculture to non-agricultural sector, but only for men (Chowdhury, Parida and Agarwal, 2022). Unpaid family work hinder the movement of women from the agricultural sector to the non-agricultural sector (Chowdhury, Parida and Agarwal, 2022)

Hypotheses

The immediate need for looking after elderly and children after a disaster occurred, increases the opportunity costs of working. Therefore, this paper expects the substitution effect to dominate. Due to social norms and role behaviors women are expected to look after the elderly and children. Also, the exacerbation of gender discrimination due to a natural disaster decreases the freedom of women and subsequently work their opportunity. These arguments are expected to have larger effect on women labour participation than the physiological advantage and the income effect. Therefore, the first hypothesis states:

Hypothesis 1: Labour participation of women decreases after a natural disaster occurred.

The second hypothesis is formulated by the fact there is a large labour demand shock for the construction sector in general (Kirchberger, 2017; Keerthiratne and Tol ,2018). According to Belasen and Polachek (2008) most reconstruction is done within two years, therefore this labor market shift is expected to only have an effect within two years after a natural disaster occurred. Therefore, the second hypothesis that is tested is:

Hypothesis 2: Labour participation in the construction sector increases within two years after a natural disaster occurred.

This paper links the labor market shift of the construction sector with the labor market shift of the agricultural, fishing, forestry, and hunting sector after a disaster occurred. This paper expects that the sharp increase in labour demand for the construction sector, mainly fills its gaps by drawing labour from the agricultural, fishing, foresting, and hunting sector. Schaner and Das (2016) state that men are the norm in construction jobs, therefore women are expected to fill the gaps the agricultural, fishing, foresting, and hunting sector. Which is even more beneficial to work in after a disaster due to expected government policy and remittances after a large disaster occurred (Klomp and Hoogezand, 2018; Kapri and Ghimire, 2020). For that reason, the third hypothesis is:

Hypothesis 3: In the agriculture, forestry, fishing, and hunting sector the participation of women increases more than the participation of men within two years after a natural disaster occurred.

Due to existing social norms and role behavior, more women are bound to their home after a disaster occurred (Neumayer and Plumper, 2007). This paper expects women to be more active in paid work that can be done from home. Therefore, this paper expects an increase in women working in the wholesale, retail, restaurant and hotel industry.

Hypothesis 4: women labour participation increases in the wholesale, retail, restaurant, and hotel industry sector after a natural disaster occurred.

Lastly, this paper expects floods to have a larger effect on women labour force participation since the disaster itself is longer lasting, leading to a longer crisis (Klomp, 2014). Next to the fact that their usual roles are more affected in this situation, as well as their employment situation in agriculture (Azra, Hossain, and Nasreen, 2013; Chowdhury, Parida and Agarwal, 2022).

Hypothesis 5: Floods have larger impact on women labour force participation than wildfires, earthquakes, and volcanic activities.

Data

Indonesian Family Life Survey

Data on individuals is coming from the Indonesian Family Life Survey (Straus et al, 2004; Straus et al, 2009; Straus et al, 2016). The IFLS conducts a survey focusing on the long-term

development of individuals in Indonesia. The survey represents eighty-three percent of the population of Indonesia living in thirteen of the twenty-six provinces in 1993. Provinces were selected to maximize representation of the population, capturing the cultural and socioeconomic diversity Indonesia (Straus et al, 2016). Within the thirteen provinces, enumeration areas were randomly chosen from a nationally representative sample frame used in 1993. The Indonesian Family Life Survey randomly selected 321 enumeration areas in the thirteen provinces, using over-sampling to provide urban-rural and Javanese-non-Javanese comparisons. Within an enumeration area a local agency office was used to randomly select a household. A household is defined as people living in the same dwelling and sharing the same cooking pot. Twenty households were selected from each urban enumeration area and thirty households were chosen from rural areas. Detailed interviews were conducted with the following household members:

- the household head and his/her spouse

- two randomly selected children of the head and spouse aged zero to fourteen

- an individual aged fifty or older and his/her spouse, randomly selected from remaining members

- for a randomly selected twenty-five percent of the households, an individual aged 15 to 49 and his/her spouse, randomly selected from remaining members.

The survey is conducted in 1993, 1997, 1998, 2000, 2007 and 2014. This paper uses the survey years 2000, 2007 and 2014 for its research[2]. In 2000 the survey took place during the whole year. In 2007 and 2014 the survey was conducted in autumn and finished in spring the following year. Therefore, the date of interview is set on the first of January of the following year for the surveys 2007 and 2014. The date of interview for 2000 is set on the first of July during that year. Individuals where gender, age, marriage status, residency, or data on paid work are missing are dropped. There remain 82,102 observations of which 16,180 are only interviewed once. 11,631 individuals are interviewed twice, and 14,220 individuals are interviewed three times. The Indonesian Family Life Survey includes, among other things, information about residence, employment, sector of primary job, gender, and role in the household.

[2] the longer ago the less information available on individuals and disasters.

The information on residence is on Kecamatan level, which is in Indonesia the administrative form of a subdistrict (Wong, 2003). It contains on average 20 to 25 villages, with as many as 60,000 residents. A Kecamatan belongs to a Kabupaten, which is a regency or city, which in turn belongs to a province (Wong, 2003).

In the survey, a respondent was able to indicate if he/she works for pay or not. Next to that, a respondent could indicate in what sector his primary occupation operated. These sectors are divided into 10 categories, namely: agriculture, forestry, fishing and hunting; mining and quarrying; manufacturing; electricity, gas, water; construction; wholesale, retail, restaurants and hotels; transportation, storage and communications; finance, insurance, real estate and business services; social services; and activities that cannot be classified. In the appendix, the figures 1 and 2 show the dispersion of age and years of schooling

EM-DAT

Data on natural disasters is retrieved from the Emergency Events Database (Guha-Sapir, Below and Hoyois, n.d.). EM-DAT distinguishes between seven groups of natural disasters, which are divided in seventeen types of natural disasters. These seventeen groups are subdivided into 44 subtypes (see appendix: table 1). Additionally, it includes detailed information on the impact of a natural disaster, including the number of deaths, the number of injured, total number of affected, and the estimated damage in US dollars. Furthermore, the data locates a natural disaster on a Kabupaten level.

This paper only uses natural disasters that are large enough to have a serious impact. In accordance with other literature a natural disaster needs to fulfill in any case one of the following four criteria, namely: at least 1,000 killed or at least 1,000 injured or at least 100,000 people affected or the damage as a result of the natural disaster needs to be as a minimum 1$ billion dollars (Gassebner, Keck and Teh, 2010; Klomp, 2016).

A natural disaster is included if it occurred seven years prior to the date of interview. This means all-natural disaster occurring between mid-1993 and 2014 in Indonesia are included in the dataset. There are nine natural disasters dropped since the region is not in the dataset of the Indonesian Family Life Survey or no one in the survey experienced this disaster. There is one natural disaster deleted, because the region of the natural disaster is missing in the EM-DAT. The total amount of natural disasters included is 26. Figure 7 in the appendix shows a map of Indonesia and indicates where all disasters took place. The map distinguishes between disaster type.

Badan Pusat Statistik

Population density per Indonesian province, minimum wage per Indonesian province and GDP per Indonesian province are all retrieved from Badan Pusat Statistik (BPS). All three variables are taken from the same years as the year of interview from the Indonesian Family Life Survey. The population density is defined per square kilometer. For Kalimantan Utara in the years 2000 and 2007, the data on population density was missing. This problem is countered by using the density of Kalimantan Utara 2014 and follow the average trend from Indonesia as a whole. Minimum wage is defined in rupiahs current market price. Data for minimum wage is missing for all years in Kalimantan Utara, this is countered by using the average minimum wage of Indonesia as a whole. Minimum wage is also missing for the regions Sulawesi Barat and Papua Barat in the year 2000, this is again solved by following the average trend of Indonesia as a whole. For GDP per province the amount is defined in billions of rupiah at the current market price. GDP is missing for Kalimantan Utara in the years 2000 and 2007 and is missing in the year 2000 for Riau, Sulawesi Barat and Papua Barat. This is again solved by following the same trend as Indonesia as a whole. The three variables are transformed into their logarithmic value, due to skewness. In the appendix, figures 3.1, 4.1 and 5.1 show the histograms for the non-logarithmic variables and figures 3.2, 4.2 and 5.2 show the dispersion of the variables in logarithmic form. This paper does not control for the number of people that are affected by a natural disaster. A pairwise correlation test between all variables suggests that this variable, people affected, is highly correlated with the natural disaster variable (appendix: table 3). This is expected, since there are not many natural disasters in the dataset. Therefore, this variable is only used as a robustness test.

Descriptive statistics

Table 4 shows general information about individuals in a descriptive statistics format, including their position in the family, age, sex, married status, and years of schooling. Next to that the table shows the average of the province related variables as: GDP, minimum wage, and population. The summary statistics gives the following information: 41.3 percent sees itself as head of household, 31.3 percent sees itself as spouse of the head of household, and 27.4 percent sees itself as another household member. The average age is just beneath forty years, the oldest is 111, and the youngest is eighteen. 52.6 percent of the participants is women and 47.4 percent is men. The average person went to school for 10.6 years and 74.2 percent is married.

Table 4: Descriptive statistics general

Variable	Obs	Mean	Std. Dev.	Min	Max
respondent	.	.	.	.	.
1:Head of household	82,102	0.413	0.492	0	1
2:Spouse of head	82,102	0.313	0.464	0	1
3:Other HH member	82,102	0.274	0.446	0	1
Age	82,102	39.093	15.442	18	111
Years schooling	71,751	10.635	5.227	1	25
Married	82,102	0.742	0.438	0	1
Sex	82,102	0.526	0.499	0	1
Log province GDP	82,102	12.168	1.345	8.49	14.382
Log province minimum wage	82,102	13.305	0.759	12.061	14.708
Log province population	82,102	6.322	1.311	2.197	9.627

Table 5 shows how many earthquakes, floods, landslides, volcanic activities, and wildfires are in the dataset. It also shows the average, median, standard deviation, minimum and maximum of indicators for the destructiveness of a disaster. The indicators shown are aid that is given in thousands of US dollars, total number of injured, total number of deaths, total damage thousands of US dollars, and total number of affected. The 26 natural disasters consist of nine earthquakes, fourteen floods, one volcanic activity, and two wildfires. From twelve natural disasters EM-DAT shows the estimated amount of aid contribution. The average aid that is contributed is around 18.4 million US$, while the median of aid contribution is around 5,5 million US$. For twenty natural disasters there is information on the amount of people injured, the average is 10,635 people and the median is 788 people. For 23 natural disasters there is information on the number of deaths, the average is around 7015,40 and the median is 68 deaths. For 23 natural disasters information on damage is included, the average is around 204,5 million US$ and the median is 590,4 million US$. 23 natural disasters include the total number of people affected, the average is around 410,2 thousand and the median is 248,8 thousand people affected.

Table 5: Descriptive statistics EM_DAT

Variable	Observations	Mean	Median	Standard deviation	Min	Max
natural disaster type				.	.	.
- Earthquake	26	0.346	-	0.485	0	1
- Flood	26	0.538	-	0.508	0	1
- Volcanic activity	26	0.038	-	0.196	0	1
- Wildfire	26	0.077	-	.272	0	1
AID Contribution in 1000 US$	12	18,416.17	5543	30476.65	687	88051
Total number of injured	20	10,635.71	788	36633.12	1	137883
Total number of deaths	23	7,015.40	68	33081.16	3	165708
Total damage adjusted in 1000 US$	23	204,488,50	590,343.5	3368808	1359	13504875
Total number of affected	23	410,201.20	248846	627860.30	2000	2500000

Table 6 shows what percentage of women in the survey work in each sector. 24.3 percent works in the agriculture, forestry, fishing, and hunting industry. 0.2 percent works in the mining and quarrying industry. 15.1 percent works in the manufacturing industry. 0.1 percent works in the electricity, gas, or water industry. 0.6 percent works in the construction industry. 34.7 percent works in wholesale, retail, restaurant, and hotel industry. 0.3 percent works in the transportation, storage and communication industry. 1.6 percent works in finance, insurance, real estate and business service industry. 22.4 percent in the social sector industry. 0.6 percent works in an industry that is not classified by the survey.

Table 7 shows what percentage of men in the survey work in each sector. 29.7 percent works in the agriculture, forestry, fishing, and hunting industry. 1.3 percent works in the mining and quarrying industry. 12.8 percent works in the manufacturing industry. 0.6 percent works in the electricity, gas or water industry. 7.7 percent works in the construction industry. 17.7 percent works in wholesale, retail, restaurant, and hotel industry. 5.3 percent works in the transportation, storage and communication industry. 5.3 percent works in finance, insurance, real estate and business service industry. 21.1 percent in the social sector industry. 0.5 percent works in an industry that is not classified by the survey.

Table 6: descriptive statistics of women in every sector

Variable	Observation	Mean	Std. Dev.	Min	Max
sector primary job	.	.	.	.	.
agriculture, forestry, fishing, and hunting	21,756	0.243	0.429	0	1
mining and quarrying	21,756	0.002	0.042	0	1
manufacturing	21,756	0.151	0.358	0	1
electricity, gas, or water	21,756	0.001	0.034	0	1
construction	21,756	0.006	0.078	0	1
wholesale, retail, restaurant and hotel industry	21,756	0.347	0.476	0	1
transportations, storage and communication industry	21,756	0.003	0.059	0	1
finance, insurance, real estate and business service industry	21,756	0.016	0.124	0	1
social sector	21,756	0.224	0.417	0	1
No classification	21,756	0.006	0.078	0	1

table 7: Descriptive Statistics of men in every sector

Variable	Observation	Mean	Standard deviation	Min	Max
sector primary job	.	.	.	.	.
agriculture, forestry, fishing, and hunting	31,394	0.297	0.457	0	1
mining and quarrying	31,394	0.013	0.115	0	1
manufacturing	31,394	0.128	0.334	0	1
electricity, gas, or water	31,394	0.006	0.080	0	1
construction	31,394	0.077	0.267	0	1
wholesale, retail, restaurant and hotel industry	31,394	0.177	0.382	0	1
transportations, storage and communication industry	31,394	0.053	0.224	0	1
finance, insurance, real estate and business service industry	31,394	0.031	0.174	0	1
social sector	31,394	0.211	0.402	0	1
No classification	31,394	0.005	0.073	0	1

Methodology.

The following equation is used to test the hypotheses:

$$Work\ for\ pay_{it} = \beta_0 + \sum_{q=0}^{n} \gamma_q\, Disaster_{kt-q} + \beta_1 gender_i + \mu_q Disaster_{kt-q} * gender_i + \beta_2 age_{it} + \beta_3 years\ of\ schooling_{it} + \beta_4 married_{it} + \beta_5 GRDP_{pt} + \beta_6 minimum\ wage_{pt} + \beta_7 population_{pt} + \lambda'_t + \eta'_c + \Omega'_h + \epsilon_{tk}$$

The dependent variable $work\ for\ pay_{it}$ indicates whether person i worked in year t or not. β_0 is the constant and γ_q is the coefficient for the disaster variable. q is a number from zero to six and indicates the number of lags. $Disaster_{kt-q}$ shows whether a disaster occurred in Kabupaten k in year t or not. β_1 is the coefficient of gender for person i. Gender is either one if person i is a woman and zero if person i is a men. μ_q is the coefficient of the interactions between disaster occurring of Kabupaten k in year t and the gender of person i. The interactions of the different lags are estimated separately. β_1 Is the coefficient of age for person i in year t. β_2 is the coefficient of years of schooling of person i in year t. β_3 is the coefficient of marriage status of person i in year t. Married is a binary variable being one if person i is married and zero otherwise. β_4 is the coefficient for the gross regional product of province p in year t. β_5 is the minimum wage of province p in year t. β_6 is the population size of province p in year t. λ'_t captures year fixed effects in year t. η'_c captures Kecamatan fixed effects of Kecamatan c. Ω'_h captures household fixed effects of household h. ϵ_{tk} is the error term.

This paper uses a binary variable which is 1 if a disruptive natural disaster occurred in the past year or 0 if that is not the case. Additionally, this paper includes lags to test the effect of disasters occurring one to two years ago, two to three years and so on, until six to seven years ago. the interaction effect of gender and disaster is estimated separately for every lag. This measure is taken because previous disasters are expected to influence the effect on work for pay, but previous interaction of gender and disaster are not. This paper includes year fixed effects to control for factors that are equal to every individual in the same year. This paper also includes Kecamatan fixed effects to control for difference between Kecamatan that are constant. Lastly, this paper includes household fixed effects controlling for differences between households that are constant. The same formula is used to estimate effects disasters have on sectors. The difference is that the dependent variable is a sector dummy instead of work for pay.

The dependent variable is work for pay. In the Indonesian Family Life Survey respondents are asked if they worked for income in the past week. The work for pay variable is a binary variable, being 1 if they did work last week and 0 otherwise. The information in which sector the individuals worked is also coming from the Indonesian Family Life Survey. The independent variable is a natural disaster. The natural disaster variable is either a binary variable, being 1 if a natural disaster occurred and 0 otherwise.

Results

This section starts off with table 8, which shows the estimation of the first hypothesis. The dependent variable is work for pay and the independent variable is a dummy for whether a disaster occurred or not. The first column of table 8 starts by showing the effect a natural disaster has on whether people are active in paid work or not. This estimation includes year and Kecamatan fixed effects. The second table adds household fixed effects to the estimation, which drops 2,776 singleton observations (Correia, 2015). The third table shows the effect of gender and the interaction between gender and disaster. The fourth table adds controls for previous disasters and the number of people affected by these disasters. The fifth table adds individual control variables, including age, married and years of schooling. Missing information on these variables drops 10,351 observations. The sixth column adds province control variables, including log GDP, log population, and log minimum wage. The seventh column adds the total amount of aid received as a robustness check. However, this drops many observations since only twelve out of 26 disasters have information on these remittances.

Table 9 shows the effect of disasters occurring longer ago than one year. The table estimates the effect of the first, third and fifth lag separately. The reason to separately estimate the interaction is because other disasters are expected to influence labour force participation, but the interaction itself is not. Therefore, it would only take out variance of the independent variable. The first column starts with estimating the effect of disasters occurring one to two years ago. The second column estimates the effect of a disaster occurring two to three years ago and the third column estimates the effect of a disaster occurring four to five years ago.

Table 8: Binary variable natural disaster variable

Dependent variable: Work for pay							
VARIABLES	Column 2	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7
$Disaster_t$	0.013	0.009	-0.004	0.108	0.040	-0.009	-0.110
	(0.009)	(0.011)	(0.014)	(0.183)	(0.199)	(0.208)	(0.312)
$Gender_i$			-0.324***	-0.324***	-0.328***	-0.328***	-0.316***
			(0.009)	(0.009)	(0.009)	(0.009)	(0.011)
$Disaster_t$			0.023	0.023	0.023	0.023	-0.039
$\times gender_i$			(0.021)	(0.021)	(0.022)	(0.022)	(0.035)
Disaster controls							
$Disaster_{t-1}$				-0.005	-0.006	-0.114	-0.064**
				(0.010)	(0.011)	(0.122)	(0.027)
$Disaster_{t-2}$				-0.051	-0.030	-0.099	0.294
				(0.040)	(0.049)	(0.143)	(0.361)
$Disaster_{t-3}$				0.009	0.016	0.003	0.015
				(0.018)	(0.018)	(0.112)	(0.023)
$Disaster_{t-4}$				0.029	0.056**	0.267	-0.104**
				(0.019)	(0.022)	(0.285)	(0.042)
$Disaster_{t-5}$				0.001	-0.004	0.205	-0.028
				(0.009)	(0.010)	(0.238)	(0.022)
$Disaster_{t-6}$				0.016	0.019	-0.042	0.019
				(0.010)	(0.012)	(0.290)	(0.020)
Additional disaster controls						People affected	Aid received
Individual control variables							
Age					0.000	0.000	0.000
					(0.000)	(0.000)	(0.000)
Years of schooling					0.005***	0.005***	0.004***
					(0.001)	(0.001)	(0.001)
Married					0.095***	0.095***	0.102***
					(0.009)	(0.009)	(0.011)
Province control variables							
Log GDP					-0.036	-0.030	-0.003
					(0.045)	(0.047)	(0.068)
Log population					-0.040	-0.042	-0.050
					(0.065)	(0.068)	(0.080)
Log minimum wage					0.059*	0.056	0.003
					(0034)	(0.040)	(0.053)
Constant	0.674***	0.677***	0.847***	0.845***	0.632	0.617	1.011
	(0.001)	(0.001)	(0.005)	(0.006)	(0.721)	(0.787)	(1.063)
Fixed effects	Year, kecamatan	Year, kecamatan, household	Year, kecamatan, household	Year, kecamatan, household	Year, kecamatan, household	Year, kecamatan, household	Year, kecamatan, household
Observations	81,885	79,326	79,326	79,326	68,751	68,751	47,099
R-squared	0.051	0.243	0.350	0.350	0.374	0.374	0.378

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 9: lagged estimation, binary natural disaster variable

	Dependent variable: Work for pay		
Column	1	2	3
$Gender_i$	-0.327***	-0.326***	-0.324***
	(0.009)	(0.009)	(0.010)
Disaster			
$Disaster_{t-1}$	-0.018		
	(0.017)		
$Disaster_{t-1}$	0.024		
$\times Gender_i$	(0.031)		
$Disaster_{t-3}$		0.016	
		(0.019)	
$Disaster_{t-3}$		-0.000	
$\times Gender_i$		(0.022)	
$Disaster_{t-5}$			0.005
			(0.013)
$Disaster_{t-5}$			-0.016
$\times Gender_i$			(0.019)
Controls			
Additional disaster controls	t, t-2, t-3, t-4, t-5, t-6	t, t-1, t-2, t-4, t-5, t-6	t, t-1, t-2, t-3, t-4, t-6
Individual control variables	Age, years of schooling, married	Age, years of schooling, married	Age, years of schooling, married
Province control variables in log	GDP, population, minimum wage	GDP, population, minimum wage	GDP, population, minimum wage
Constant	0.628	0.627	0.627
	(0.721)	(0.721)	(0.721)
Fixed effects	Year, kecamatan, household	Year, kecamatan, household	Year, kecamatan, household
Observations	68,751	68,751	68,751
R-squared	0.374	0.374	0.374

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

The results in table 8 are insignificant and gradually adding control variables do not influence this significance. Table 9 shows that the disaster lags also show insignificant results. There are two possible explanations for these results. One explanation is that there is simply no effect of a disaster on labour participation. The other explanation is that the estimation falsely fails to reject the null hypothesis, also referred to as a type II error. Following the literature, a type II error is much more likely than no effect. It is rather unlikely that an exogenous shock as a disaster has no effect on labour participation at all. Next to that, there are conceivable explanations for this type II error which are discussed at the end of the paper in the limitations section.

Table 10, table 11, and table 12 show the effect a disaster has on a specific sector. These estimations only include people that work. 15,601 observations were dropped since these people did either not work or the sector was missing. 369 observations are dropped since they are only singleton observations (Correia, 2015). The first column of the three tables tests the effect a natural disaster has on labour participation in a specific sector. The first column also includes the effect of the first, third, and fifth lag. The second column shows the effect a disaster has on labour force participation in a specific sector making a distinction between gender. The third column makes this distinction for the first lag, the fourth column makes this distinction for the third lag and the fifth column makes this distinction for the fifth lag.

Table 10: effect on construction

Dependent variable: construction					
Column	1	2	3	4	5
$Disaster_t$	0.003	0.004			
	(0.005)	(0.008)			
$Gender_i$		-0.074***	-0.074***	-0.077***	-0.075***
		(0.005)	(0.005)	(0.005)	(0.006)
$Disaster_t$		-0.004			
$\times Gender_i$		(0.011)			
$Disaster_{t-1}$	0.005		0.005		
	(0.013)		(0.024)		
$Disaster_{t-1}$			-0.001		
$\times Gender_i$			(0.027)		
$Disaster_{t-3}$	-0.008			-0.015	
	(0.008)			(0.011)	
$Disaster_{t-3}$				0.024**	
$\times Gender_i$				(0.009)	
$Disaster_{t-5}$	-0.004				-0.005
	(0.004)				(0.007)
$Disaster_{t-5}$					0.005
$\times Gender_i$					(0.009)
Controls					
Additional disaster controls	t-1, t-2, t-3, t-4, t-5, t-6	t-1, t-2, t-3, t-4, t-5, t-6	t, t-2, t-3, t-4, t-5, t-6	t, t-1, t-2, t-4, t-5, t-6	t, t-1, t-2, t-3, t-4, t-6
People affected	Included	Included	Included	Included	included
Individual control variables	Age, years of schooling, married	Age, years of schooling, married	Age, years of schooling, married	Age, years of schooling, married	Age, years of schooling, married
Province control variables in log	GDP, population, minimum wage	GDP, population, minimum wage	GDP, population, minimum wage	GDP, population, minimum wage	GDP, population, minimum wage
Constant	0.244	0.243	0.244	0.255	0.243
	(0.278)	(0.309)	(0.307)	(0.309)	(0.309)
Fixed effects	Year, kecamatan	Year, kecamatan	Year, kecamatan	Year, kecamatan	Year, kecamatan
Observations	59,618	52,781	52,781	52,781	52,781
R-squared	0.056	0.090	0.090	0.090	0.090

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 11: effect on agriculture, forestry, fishing, and hunting

	Dependent variable: agriculture, forestry, fishing, and hunting				
Column	1	2	3	4	5
$Disaster_t$	-0.017*	-0.205			
	(0.009)	(0.162)			
$Gender_i$		-0.060***	-0.061***	-0.059***	-0.063***
		(0.008)	(0.008)	(0.008)	(0.008)
$Disaster_t$		0.003			
$\times Gender_i$		(0.017)			
$Disaster_{t-1}$	-0.001		-0.014		
	(0.010)		(0.011)		
$Disaster_{t-1}$			0.031*		
$\times Gender_i$			(0.012)		
$Disaster_{t-3}$	0.003			0.005	
	(0.017)			(0.019)	
$Disaster_{t-3}$				0.001	
$\times Gender_i$				(0.018)	
$Disaster_{t-5}$	0.004				-0.011
	(0.008)				(0.009)
$Disaster_{t-5}$					0.036**
$\times Gender_i$					(0.014)
Controls					
Additional disaster controls	t-2, t-3, t-5	t-1, t-2, t-3, t-4, t-5, t-6	t, t-2, t-3, t-4, t-5, t-6	t, t-1, t-2, t-4, t-5, t-6	t, t-1, t-2, t-3, t-4, t-6
People affected	Included	Included	Included	Included	included
Individual control variables	Age, years of schooling, married	Age, years of schooling, married	Age, years of schooling, married	Age, years of schooling, married	Age, years of schooling, married
Province control variables in log	GDP, population, minimum wage	GDP, population, minimum wage	GDP, population, minimum wage	GDP, population, minimum wage	GDP, population, minimum wage
Constant	0.414	0.444	0.435	0.444	0.438
	(0.665)	(0.668)	(0.669)	(0.668)	(0.668)
Fixed effects	Year, kecamatan	Year, kecamatan	Year, kecamatan	Year, kecamatan	Year, kecamatan
Observations	52,781	52,781	52,781	52,781	52,781
R-squared	0.421	0.425	0.425	0.425	0.425

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 12: effect on wholesale, retail, restaurant, and hotel

Dependent variable: wholesale, retail, restaurant, and hotel.					
Column	1	2	3	4	5
$Disaster_t$	-0.004	0.021			
	(0.011)	(0.013)			
$Gender_i$		0.171***	0.167***	0.169***	0.170***
		(0.008)	(0.008)	(0.008)	(0.008)
$Disaster_t \times Gender_i$		-0.042*			
		(0.019)			
$Disaster_{t-1}$	-0.016		-0.025		
	(0.015)		(0.019)		
$Disaster_{t-1} \times Gender_i$			0.024		
			(0.023)		
$Disaster_{t-3}$	-0.002			-0.005	
	(0.014)			(0.016)	
$Disaster_{t-3} \times Gender_i$				-0.010	
				(0.022)	
$Disaster_{t-5}$	0.002				0.008
	(0.014)				(0.015)
$Disaster_{t-5} \times Gender_i$					-0.026
					(0.019)
Controls					
Additional disaster controls	t-1, t-2, t-3, t-4, t-5, t-6	t-1, t-2, t-3, t-4, t-5, t-6	t, t-2, t-3, t-4, t-5, t-6	t, t-1, t-2, t-4, t-5, t-6	t, t-1, t-2, t-3, t-4, t-6
People affected	Included	Included	Included	Included	included
Individual control variables	Age, years of schooling, married	Age, years of schooling, married	Age, years of schooling, married	Age, years of schooling, married	Age, years of schooling, married
Province control variables in log	GDP, population, minimum wage	GDP, population, minimum wage	GDP, population, minimum wage	GDP, population, minimum wage	GDP, population, minimum wage
Constant	-0.480	-0.572	-0.570	-0.567	-0.559
	(0.608)	(0.608)	(0.604)	(0.606)	(0.607)
Fixed effects	Year, kecamatan	Year, kecamatan	Year, kecamatan	Year, kecamatan	Year, kecamatan
Observations	52,781	52,781	52,781	52,781	52,781
R-squared	0.116	0.151	0.151	0.151	0.151

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

The tables 10, 11 and 12 mostly show insignificant results. However, there are some notable exceptions. Table 10 shows that three to four years after a disaster occurred women have a 0.024 higher probability than the increase in probability of men working in the construction sector. The columns three and five of table 11 show that women increase their participation in the agriculture, forestry, fishing and hunting sector relative to men one to two and five to six years after a disaster occurred. One to two years after a disaster occurred women have a 0.031 higher probability than the increase in probability of men working in the agriculture, forestry, fishing and hunting sector. Four to five years after a disaster occurred this probability is 0.035. Therefore, this paper founds some evidence for the third hypothesis stating that women are drawn to the agriculture, forestry, fishing, and hunting sector. however, this paper does not show evidence for the short-term effect of men being drawn to the construction sector mainly from the agriculture, forestry, fishing, and hunting sector. The insignificant figures in table 11 seem highly unlikely, since there has to be an immediate demand shock in the construction sector after a destructive disaster occurs (Kirchberger, 2007; Belasen and Polacheck, 2008; Belasen and Polacheck, 2009; Klomp, 2014; Keerthiratne and Tol, 2018). The fourth hypothesis tested in table 12 shows that a year after a disaster occurred, women decrease their probability to work in the wholesale, retail, restaurant and hotel relative to men with 0.042. Possible explanations for this opposite result is that shops at home might be destroyed by the natural disaster or running a shop near the house is too much workload while taking care of the household.

Table 13, table 14, table 15, table 16 and table 17 are in the appendix. Table 13 shows the effect of a natural disaster on the remaining sectors, including all lags. All control variables are included, namely gender, age, years of schooling, married, GDP, population, minimum wage. Table 14 shows the interaction effect between gender and natural disaster on the remaining sectors. Again, all control variables are included as well as the disaster lags. Table 15 shows the first lag of this effect, table 16 the third lag and table 17 the fifth lag. Overall, the results of these tables are the same. Sometimes there is small significant effect on a sector after a disaster occurred.

Table 18: Disaster types

Dependent variable: Work for pay							
Column	1	2	3	4	5	6	7
Years prior to interview	0-1 year	1-2 year	2-3 year	3-4 year	4-5 year	5-6 year	6-7 year
$gender_i$	-0.327***	-0.327***	-0.326***	-0.326***	-0.326***	-0.324***	-0.322***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	0.006	(0.009)
$Earthquake$	0.018	-0.055***	-0.301***	0.005		(0.019)	
	(0.011)	(0.014)	(0.017)	(0.022)		-0.009	
$Earthquake \times gender_i$	0.021	0.104***	0.515***	0.017		(0.024)	
	(0.037)	(0.028)	(0.011)	(0.040)		0.005	
$Flood$	-0.009	0.004			0.021*	(0.016)	0.031*
	(0.018)	(0.022)			(0.013)	-0.031	(0.014)
$Flood \times gender_i$	0.013	-0.027			0.022	-0.031	-0.029
	(0.025)	(0.031)			(0.029)	(0.022)	(0.017)
$Wildfire$			-0.027	0.019			
			(0.046)	(0.024)			
$Wildfire \times gender_i$			-0.005	-0.005			
			(0.051)	(0.023)			
$Volcanic\ activity$					0.024		
					(0.019)		
$Volcanic\ activity \times gender_i$					0.119***		
					(0.016)		
Controls							
Disaster lags	t-1, t-2, t-3, t-4, t-5, t-6	t, t-2 t-3, t-4, t-5, t-6	t, t-1, t-3, t-4, t-5, t-6	t, t-1, t-2, t-4, t-5, t-6	t, t-1, t-2, t-3, t-5, t-6	t, t-1, t-2, t-3, t-4, t-6	t, t-1, t-2, t-3, t-4, t-5
Individual control variables	Age, years of schooling, married	Age, years of schooling, married	Age, years of schooling, married	Age, years of schooling, married	Age, years of schooling, married	Age, years of schooling, married	Age, years of schooling, married
Province control variables	GDP, population, minimum wage	GDP, population, minimum wage	GDP, population, minimum wage	GDP, population, minimum wage	GDP, population, minimum wage	GDP, population, minimum wage	GDP, population, minimum wage
Constant	0.581	0.713	0.613	0.612	0.593	0.597	0.616
	(0.774)	(0.868)	(0.786)	(0.787)	(0.788)	(0.784)	(0.790)
Fixed effects	Year, kecamatan	Year, kecamatan	Year, kecamatan	Year, kecamatan	Year, kecamatan	Year, kecamatan	Year, kecamatan
Observations	68,751	68,751	68,751	68,751	68,751	68,751	68,751
R-squared	0.374	0.374	0.374	0.374	0.374	0.374	0.374

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 18 distinguishes between four types of disaster namely: earthquake, flood, wildfire, and volcanic activity. The tables shows that not all disaster types occurred in every lag. For example, no wildfire occurred zero to one year prior to an interview, therefore no estimation is made. The paper mainly shows insignificant results, but there are some exceptions. The second column shows that the probability of women to participate in paid work increases by 0.049 (0.104-0.055). Men on the other hand decrease their labour participation by 0.055 one to two years after an earthquake. The third column shows that the probability of men being active in paid work decreases by 0.301 and the probability of women being active in paid work increases by 0.214 (-0.301+0.515). This can be explained by the idea that men work relatively more outside of the house. Workplaces outside of the house might be destroyed by the destructive power of an earthquake, leading to decrease in labour participation. Women might be able to compensate this decrease in men labour participation. The fifth column shows that a flood increases the probability of being active in paid work with 0.167 for men but does not show a significant effect for the probability of women being active in paid work. The fifth column also shows that after a volcanic eruption increases the probability of men being active in paid work by 0.283 and women being active in paid work by 0.402 (0.283+0.119). There is no proof to confirm the fifth hypothesis that floods have a larger impact than earthquakes, since the estimates do not show significant figures in the same column.

Discussion

This paper aimed to provide an answer to whether labour participation among women is negatively affected after a disaster occurred. Additionally, this paper tried to show the effects on different labour sectors. Lastly, this paper tested the different effect different types of disasters can have on labour participation. The results show in contrast with the expectations mainly non-significant results. There are some conceivable explanations for this insignificant. First of all, there are two possibilities either a natural disaster does not increase or decrease labour participation or this research falsely fails to reject the null hypothesis. There are several reasons to assume a type II error.

First of all, the cut-off point used to determine if a natural disaster is severe enough. There is much heterogeneity among the severity indicators of natural disasters. For example, the minimum amount of people injured is one, median amount of people injured is 788, the average is 10,635.71, and the maximum is 137,883. On top of that there are only 26 disasters in the dataset within a period of 21 years. This paper did include the amount of people affected to control for the severity of a disaster, but this paper did not include a control variable for the

size of a geographical area of a disaster. A natural disaster has a greater impact if many people are affected on a small area than if many people are affected on a large area. Next to that, the effect of a disaster is not equally divided within the Kabupaten. For example, a river flood probably has a large impact on people living near the river, but a large part of the people living in a certain Kabupaten might not live near a river. Similarly for an earthquake, people living around the epicentre of an earthquake are hit differently than other people living farther away in the same Kabupaten. This way these people are assigned to have experienced a natural disaster, but in reality, these people did not. Furthermore, a disaster covering multiple Kabupaten do not hit these different Kabupaten equally. This influences the results since people living in these different Kabupaten are all treated as if they experienced a natural disaster.

Another limitation is that there are only three points in time, which are seven years apart. Therefore, this paper compares the effect of disaster X one year ago and disaster Y two years ago. Effects of the same disaster could not be followed over time only if this paper is interested in the effect seven years later. Therefore, the effects of different disasters are compared and not the effect of the same disaster with itself. Another limitation is that there are only 26 disasters in the dataset covering a period of 21 years. This paper might also suffer from a sampling error, people affected by a natural disaster might be harder to find due to migration. Not only people that are affected but also people moving out due to changing labour demand. Therefore, people that did not change jobs might be overrepresented and people that did change jobs might be underrepresented.

Another problem is that natural disaster-prone countries are better in minimizing the welfare costs (Barro, 2006; Barro 2009). Therefore, women labour force participation rates might be less affected in Indonesia since its society is already used to accommodating to natural disasters now and then. Therefore, the generalizability of the results is disputable.

Lastly, this paper did find significant values for women increasing their participation in the agriculture, forestry, fishing, and hunting more than men do. Therefore, this paper contributes by showing that women are relatively more drawn to this sector after a disaster occurred than men (Kirchberger, 2017; Schaner and Das, 2016). But more research is needed to confirm that this effect occurs because men are driven out of this sector and into the construction sector (Kirchberger, 2017; Belasen and Polacheck, 2008; Belasen and Polacheck, 2009). This paper also found some evidence that women are less likely to run a business from home. This is in contrast with expectations because it is easier to care for the household when working from

home. There are multiple possibilities, for example shops can be destroyed by the natural disasters and therefore women drop out of this sector. It is also possible that taking care of the household after a natural disaster is too much workload. Or women work more outside of the house after a natural disaster, since the village needs to be rebuilt. Next to that, this paper found significant values for the different disaster types. This part does find evidence that disasters do influence labour participation but fails to give an answer to whether floods have a different impact than earthquakes.

Future research

This paper used a certain cut-off point to measure the severity of a natural disaster. Future research should consider multiple cut-off points, to get a better understanding at what point a natural disaster is disrupting employment. However, more data is needed to be able to do this. Therefore, using data from multiple countries might be a way to have enough disasters and enough people to conduct this research. This way, future research can also find answers to the different effects different types of disasters has. Next to that it is important to know if women actually increase or decrease working after a natural disaster occurs. As well as if women are more likely to give up their job to run a business at home. If that is the case, women pay the real price of disasters by giving up their career opportunities.

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Appendix

Figure 1

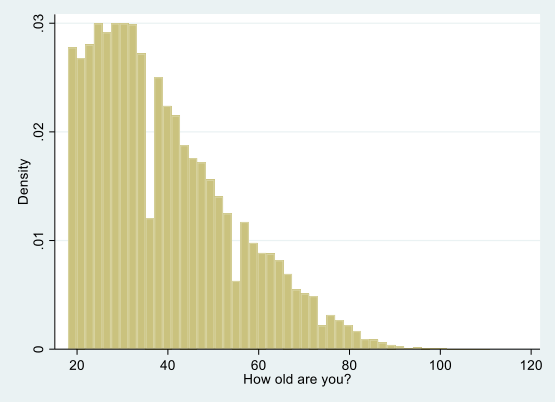


Figure 2

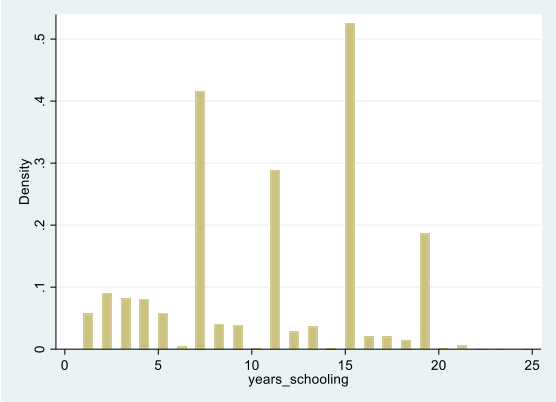


Figure 3.1

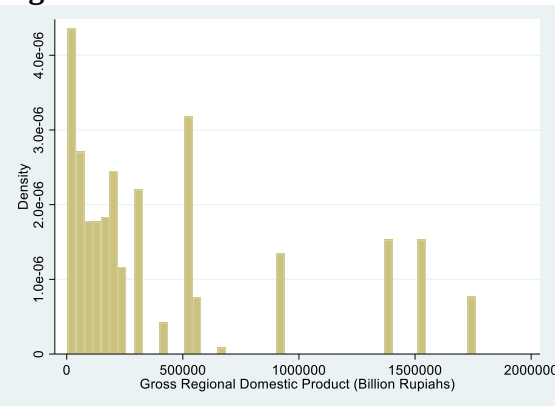


Figure 3.2

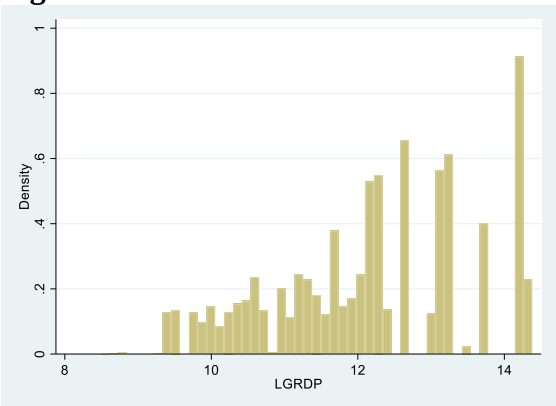


Figure 4.1

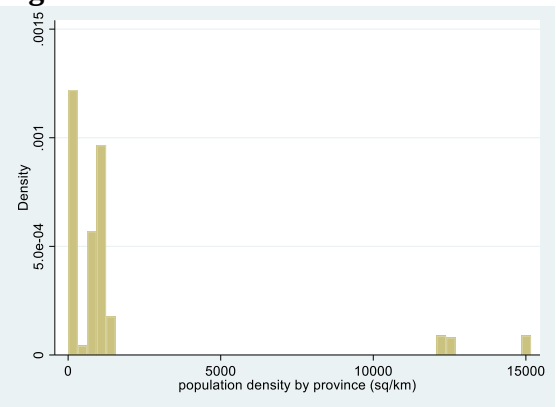


Figure 4.2

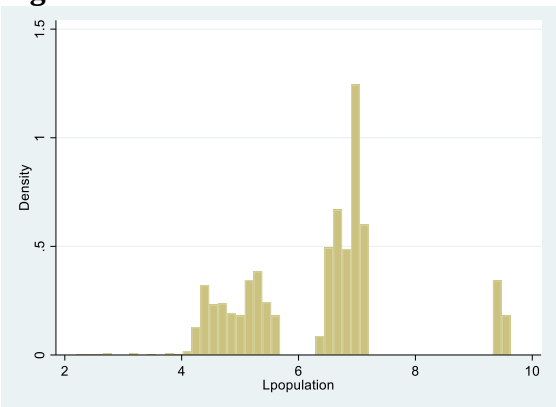


Figure 5.1

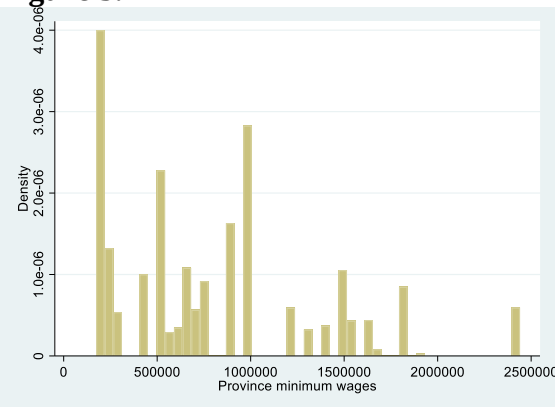


Figure 5.2

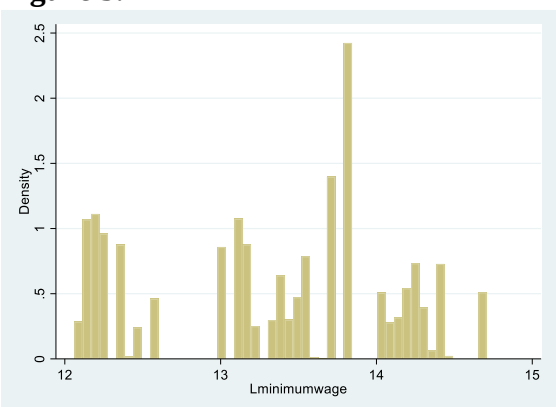


Table 1: Natural disasters

geophysical	Volcanic activity	Ash fall lahar Pyroclastic flow Lava flow
	Mass movement	Rockfall landslide avalanche subsidence
	Earthquake	Ground movement tsunami
Biological	epidemic	Bacterial disease Fungal disease Parasitic disease Prion diseases Viral disease unkown
	Insect infestation	Grasshopper Locust Worms
	Animal accident	
Climatological	Wildfire	Forest fire Land fire Urban fire
	Glacial lake outburst	
	Drought	Drought
Hydrological	Wave action	Rogue wave Seiche
	landslide	Avalanche Landslide subsidence Rockfall Mudslide
	Flood	Coastal flood Flash flood Ice jam flood Riverine flood
meteorological	Extreme temperature	Cold wave Heat wave Severe winter conditions
	Fog	
	storm	Convective storm Extra-tropical storm Tropical cyclone
Extra terrestrial	Impact	airbust
	Space weather	Energetic particles Geomagnetic storm Schockwave Collision

Table 3: pairwise correlation test

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) disaster	1.000										
(2) work for pay	-0.001	1.000									
(3) sex	0.007	-0.339	1.000								
(4) age	-0.017	0.027	-0.048	1.000							
(5) years of schooling	0.024	0.004	-0.038	-0.330	1.000						
(6) married	-0.021	0.081	0.004	0.178	-0.096	1.000					
(7) Log GDP	0.111	-0.014	0.007	0.003	0.107	0.037	1.000				
(8) Log population	0.021	-0.010	-0.006	0.035	0.118	-0.009	0.333	1.000			
(9) Log minimum wage	0.025	0.043	0.006	0.040	0.107	0.050	0.574	-0.113	1.000		
(10) Log aid contributed	-0.128	0.029	-0.005	0.098	0.084	-0.015	-0.372	0.409	-0.127	1.000	
(11) Log affected	-0.077	0.002	-0.007	0.054	0.124	-0.016	0.099	0.893	-0.184	0.690	1.000

Table 13: Effect of natural disaster on different sectors

VARIABLES	Manu-facturing	Transport, storage, and communication	Finances, insurance, real estate, business services	Manu-facturing	Electricity, gas, water
$Disaster_t$	0.010	0.005	-0.001	-0.004	0.002
	(0.009)	(0.004)	(0.005)	(0.010)	(0.004)
$Disaster_{t-1}$	0.018	-0.002	0.026**	-0.042*	0.010
	(0.015)	(0.004)	(0.009)	(0.020)	(0.005)
$Disaster_{t-2}$	-0.021	-0.009	0.001	-0.014	-0.012*
	(0.021)	(0.011)	(0.008)	(0.023)	(0.005)
$Disaster_{t-3}$	0.001	-0.000	0.007	-0.004	0.004
	(0.013)	(0.005)	(0.006)	(0.012)	(0.002)
$Disaster_{t-4}$	0.005	0.001	-0.020**	0.021	-0.010*
	(0.013)	(0.008)	(0.007)	(0.017)	(0.005)
$Disaster_{t-5}$	-0.027**	0.004	0.009	0.008	0.010
	(0.008)	(0.004)	(0.006)	(0.010)	(0.007)
$Disaster_{t-6}$	0.001	-0.008*	0.005	-0.001	-0.006
	(0.011)	0.005	-0.001	-0.004	0.002
Constant	0.654	-0.480	-0.026	-0.850*	1.192*
	(0.520)	(0.608)	(0.205)	(0.381)	(0.570)
Observations	52,781	52,781	52,781	52,781	52,781
R-squared	0.152	0.116	0.051	0.088	0.175

Standard errors in parentheses

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

Table 14: Gendered effect of natural disaster on different sectors (0-1 years)

VARIABLES	Manu-facturing	Transport, storage, and communication	Finances, insurance, real estate, business services	Social services	No class-ification
$Disaster_t$	-0.008	0.006	-0.007	0.002	0.003
	(0.013)	(0.006)	(0.005)	(0.010)	(0.004)
$Disaster_t \times Gender_i$	0.042*	-0.004	0.015***	-0.014	-0.002
	(0.020)	(0.007)	(0.003)	(0.005)	(0.001)
Constant	0.653	-0.003	-0.839**	1.176**	-0.265
	(0.519)	(0.203)	(0.381)	(0.570)	(0.173)
Observations	52,781	52,781	52,781	52,781	52,781
R-squared	0.153	0.069	0.090	0.176	0.050

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 15: Lagged gendered effect of a natural disaster on different sectors (1-2) years

VARIABLES	Manu-facturing	Transport, storage, and communication	Finances, insurance, real estate, business services	Social services	No class-ification
$Disaster_{t-1}$	0.030**	-0.007	0.040**	-0.041**	0.012*
	(0.011)	(0.007)	(0.014)	(0.019)	(0.006)
$Disaster_{t-1} \times Gender_t$	0.004	0.027*	0.000	0.010	-0.003
	(0.005)	(0.016)	(0.002)	(0.008)	(0.002)
Constant	0.654	-0.480	-0.026	-0.850*	1.192*
	(0.520)	(0.608)	(0.205)	(0.381)	(0.570)
Observations	52,781	52,781	52,781	52,781	52,781
R-squared	0.152	0.116	0.051	0.088	0.175

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 16: Lagged gendered effect of a natural disaster on different sectors (3-4 years)

VARIABLES	Manu-facturing	Transport, storage, and communication	Finances, insurance, real estate, business services	Social services	No class-ification
$Disaster_{t-3}$	0.016	0.007	-0.001	-0.011	0.004
	(0.014)	(0.008)	(0.006)	(0.012)	(0.002)
$Disaster_{t-3} \times Gender_i$	0.042*	-0.004	0.015**	-0.014	-0.002
	(0.020)	(0.007)	(0.003)	(0.005)	(0.001)
Constant	0.628	-0.007	-0.834*	1.186*	-0.264
	(0.518)	(0.203)	(0.381)	(0.570)	(0.173)
Observations	52,781	52,781	52,781	52,781	52,781
R-squared	0.153	0.069	0.090	0.176	0.050

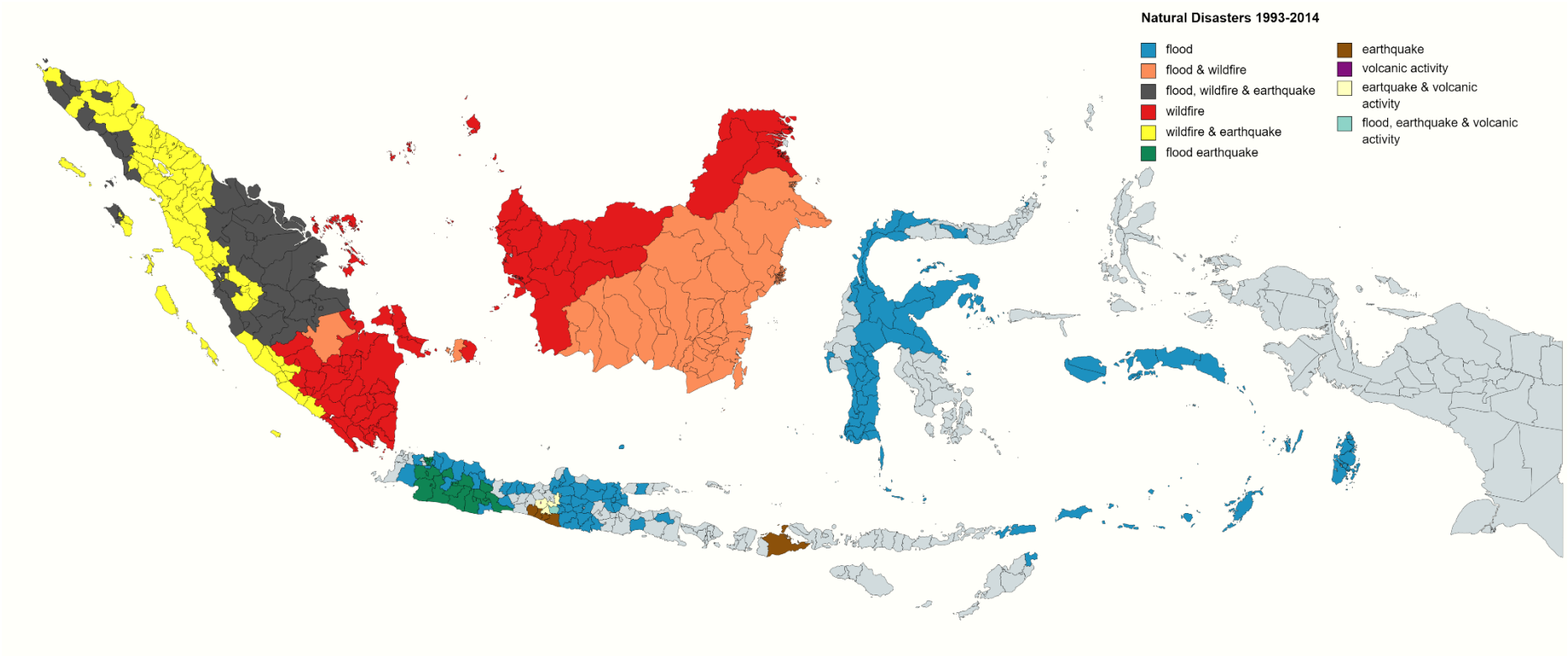
Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 17: Lagged gendered effect of a natural disaster on different sectors (5-6 years)

VARIABLES	Manu-facturing	Transport storage, and communication	Finances, insurance, real estate, business services	Social services	No class-ification
$Disaster_{t-5}$	-0.021	0.006	0.022	-0.010	0.011
	(0.012)	(0.006)	(0.010)	(0.011)	(0.006)
$Disaster_{t-5} \times Gender_i$	0.017	0.000	-0.037***	-0.033***	0.023***
	(0.019)	(0.003)	(0.006)	(0.006)	(0.007)
Constant	0.647	-0.001	-0.837	1.172	-0.264
	(0.520)	(0.203)	(0.380)	(0.571)	(0.173)
Observations	52,781	52,781	52,781	52,781	52,781
R-squared	0.152	0.069	0.091	0.176	0.050

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Figure 6


Natural Disasters 1993-2014
flood
flood & wildfire
flood, wildfire & earthquake
wildfire
wildfire & earthquake
flood earthquake
earthquake
volcanic activity
eartquake & volcanic activity
flood, earthquake & volcanic activity