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Post-earthquake short-run labor income shifts. What happens with the distribution of wages after an earthquake?

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ABSTRACT

In this article we explore whether a strong earthquake (*Manabí* and *Esmeraldas* provinces, Ecuador, April 16th, 2016) had a distributional effect in labor income. We use survey micro-data and exploit the exogenous nature of the shock with an empirical strategy based on a combination of matching, difference in difference (DID) and quantile regression (QR) methods using three earthquake intensity measures to define our treatment group (Peak Ground Acceleration, PGA; Modified Mercalli Intensity, MMI; Peak Ground Velocity, PGV). We find a short-run distributional effect of the earthquake favorable to the poorest workers in the most seismic areas, with higher growth rates for female workers in the first deciles. Quantile difference in differences (QDID) estimates for matched individuals show increases of approximately 12% in the first decile of labor income and 9.5% in the second one. Our results suggest that some opportunities might arise for lower-paid workers if economic incentives are directed towards the most affected areas.

1. Introduction

On April 2016 a 7.8 Mw (moment magnitude) earthquake struck the coastline of Ecuador at a 20 Km depth. The provinces of *Manabí* and *Esmeraldas* received the bulk of physical damages and social disruption. As a result of the earthquake, 671 people died and the estimated reconstruction cost was USD $3,334 million (Committee for Reconstruction and Productive Reactivation 2016)[1]. The objective of this article is to understand the short-run wage shifts that were experienced by individuals located in areas stricken by this earthquake, focusing specifically on the distribution of labor income. We focus on the short-term wage distribution and changes that were measured before and after the earthquake, considering that we can confidently assume randomness for their occurrence in Ecuador [1].

Our research provides empirical evidence of labor income shifts beyond the average effects often seen in some academic and policy-oriented disaster studies (Belasen and Polachek 2009; [2]. We explore the distributional effects associated to the Ecuadorian earthquake using micro data at the individual worker level. We empirically analyze a short-run individual panel survey that contains rich labor market information for people and households before and after the event (December 2015 and December 2016, respectively). We merge the panel data with the United States Geological Survey (USGS) earthquake Shakemaps, which allows us to obtain average

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intensity measures per canton[2].

The motivation for our research is threefold. Firstly, we follow-up past research recommendations that point out the importance of disentangling changes in the wage structure after a disaster. Secondly, Latin American labor markets have many particularities in female participation, formality and heterogeneity that make them interesting case studies to understand the effects of shocks in many socioeconomic dimensions, wage structure changes have not been studied in detail for disaster scenarios at regional and local scales, or using gender-specific models [3].

Our empirical strategy combines three econometric techniques: matching, quantile regression (QR), and difference in differences (DID). As we show below, we found earthquake distributional effects on labor income for workers located in the areas with major earthquake intensity, and for workers who belong to the first quantiles of distribution (lower wages). In the lower quantiles, the earthquake seems to have triggered a positive wage effect, as labor income increased for workers in the most affected areas compared to our control group, after controlling by worked hours and other variables. This effect was observed both for male and female workers, but growth rates were higher for females. We discuss in the final section the policy implications of our findings.

The next section briefly reviews the relevant literature around disasters and labor markets that motivate our research, followed a context section regarding the April 2016 earthquake and a brief description of the Ecuadorian labor market. We then present the data, methodology and results sections. In the final section we discuss our results, limitations and policy recommendations.

2. Literature review

Our article builds upon the interdisciplinary literature of disaster studies that tries to understand broad societal changes in these scenarios, specifically around labor markets [2,4–8]. Even though some findings in this literature have helped us to better understanding employment and sectoral shifts [2,6], they have also left us important unanswered questions regarding distributional aspects and gender effects on employment and wages.

2.1. Labor markets and disasters

Our current knowledge about the short-, medium- and long-term reactions of labor markets to different types of natural hazards is still incomplete. Specific questions in this realm were initially approached using cross-country aggregate data, macroeconomic models and broad definitions of disasters [9,10], yet studies that tried to analyze labor market effects within regions or countries have shown both positive and negative effects in the short and long run [2,4,7,8,11–13].

All these studies look at specific effects on rich and poor countries using different data aggregations and timespans, but the real challenge is to look for specific labor market adjustments that become visible in disaster scenarios. While some studies do find evidence of downward supply shifts after an earthquake [2], the diversity of disaster types, environments, time-spans, political, social and economic conditions in each country or region have motivated social scientists to understand labor market changes in more detail.

Disasters are increasingly seen as events and processes that showcase societies' strengths and weaknesses, and their impacts have more to do with preexisting inequalities than random misfortune [14]. Current research questions are mostly focused on the complexities surrounding disasters and societies, which motivates us to dig deeper into wage structure changes in the short-run, since just a few studies have considered distributional aspects in post-disaster societies [15].

We are particularly interested in studies that have answered the most pressing questions regarding labor markets, such as employment, demand shifts and structural changes. Local impacts on employment have been found in different countries [2,7,8,13,16], as well as other effects directly related to labor markets, such as informality, economic diversity [17], resilience [5,18] and reconstruction efforts [19,20]. The probability of informality, for instance, increased during the Ecuadorian earthquake we are studying [1], but the Chilean 2010 earthquake showed no significant increases in the share of informal workers [8]. Similarly, spatial labor demand [13] and sectoral shifts [2,6] have been observed in rich and poor countries, sometimes showing that increased labor demand on one area, might have effects on the structure of regional or national labor markets.

In summary, the link between earthquakes and labor markets has been mostly focused on sectoral changes, job transitions, adjustment mechanisms and how wages and employment behave in general terms. Focusing on wage structure changes after earthquakes would directly contribute to explore distributive aspects of regional labor markets, motivating us to fill that gap in the literature.

2.2. Disasters and societies

Our motivation also comes from the disaster studies literature, since there are other social issues that influence our research around labor markets after an earthquake. Governance, for instance, has been identified as a key factor that affects disaster risk reduction [21–23] and plays a very important role in the discussion of our results and policy recommendations.

Similarly, the risk of increased disasters has become more prevalent and potentially damaging in recent years due to climate change [24], social conflict [25] and the recent global pandemic [26]. These global and local processes have led us to increase focus on how institutional factors also influence workers' outcomes in times of crises. It is true that economic analysis of disasters often considers both direct and indirect costs when their impact is assessed [27,28], yet there are dimensions of well-being that are inherently difficult to capture and still influence societies and labor markets broadly, such as the definitions of social vulnerability to disasters [29–31],

[2] Cantons are the second smallest subnational geographic units in Ecuador and form provinces when grouped together. They are equivalent to counties or municipalities in other countries.

impacts on subjective well-being [32–35], social capital and the displacement of communities [22,36–38]. These studies show that disasters are very complex issues inherently tied to the societies they affect, consequently we will address some of these aspects while discussing the limitations of our approach.

Our article also contributes to a broad set of literature within the fields of disaster studies and applied economics that highlights issues in governance, vulnerability, inequality and other forms of social exclusion [23,39–41]. Some authors have found that income inequality might be reduced if income in the richest quintiles decreases [15], but in general, most studies conclude that the poor and vulnerable suffer the most from disasters [42,43]. Women are also disproportionally affected by disasters, so gender perspectives are increasingly seen as a critical dimension in the fields of social science research relevant to this article [3]. These complexities have motivated us to replicate our empirical strategy for male and female workers separately, giving us a broader insight into their different post-earthquake wage changes and their distribution.

3. Context

This section presents the context of our study. First, we are going to very briefly describe the April 2016 Ecuadorian earthquake, to understand both the context and the economic policies that the government adopted. Then, we will shortly describe the Ecuadorian labor market to understand the economic context of our case study.

3.1. April 2016 ecuadorian earthquake

The hypocenter of the earthquake was located off the coast of Manabí and Esmeraldas provinces, which were the most affected regions in terms of infrastructure damage and social disruption. The disaster left a total of 671 lives lost, being Manabí the most affected province. In the three days after the earthquake more than 4,800 people received health care, and 113 individuals were rescued alive.

In general, the estimated reconstruction costs were around $USD 3,344 million, distributed across the social, infrastructure and productive sectors [44]. The areas most affected by the disaster were already vulnerable, both physically and socio-economically. The national government developed actions and regulations to help the recovery of the affected areas. Specifically, a law that raised solidarity contributions was passed in the national assembly [45], and the value added tax was temporarily increased by 2% points for every province, except for Manabí and Esmeraldas. Incentives were established for new productive investments in these two provinces.

Government reports indicate that more than 44,000 indirect and direct jobs were created a year after the earthquake, and by 2018, 2,876 million $USD were allocated for reconstruction, productive reactivation and emergency management (Committee for Reconstruction and Productive Reactivation[3] 2016; [7].

3.2. Ecuadorian labor market

Ecuador is a dollarized economy and is officially classified as an upper middle-income country, according to the World Bank. In reality, the country is highly heterogeneous, both socioeconomically and geographically. The working age population (WAP) consisted of 11.4 million people in December 2015, and the economic active population (EAP) were 7.5 million people[4]. Most people in the EAP are urban (68%), and the average unemployment rate[5] was 4.8% by the end of 2015 [46].

One of the most important characteristics of this labor market is that a large part of it works in the informal sector[6] (40.4% in December 2015). It is important to highlight that the majority of workers are males (59.9%), and their average weekly hours (41.7) are higher than female workers (35.5 h).

In Fig. 1, we present the country labor income evolution using cross section ENEMDU. Note that there is a persistent labor income gap between female and male workers, for example in December 2016, male workers earned on average 533 dollars, while women earned 419 USD. This difference alongside long-entrenched cultural patterns of gender-specific occupations, and more specifically, the high levels of gender time-use inequality that Ecuadorian households report [47], motivate us to estimate separate models for male and female workers. This figure shows a wage reduction between December 2015 (pre-earthquake) and December 2016 (post-earthquake) in the country average labor income[7], and the slump is similar in magnitude both for Ecuadorian males and females.

4. Data

We use a short-run individual panel dataset based on the National Survey of Employment, Unemployment and Underemployment (ENEMDU) collected by the Ecuadorian Institute of Statistics and Census[8] [48]. This survey contains detailed information of socio-economic characteristics of individuals both for the pre-earthquake and post-earthquake periods (December 2015 and 2016,

[3] Comité para Reconstrucción y Reactivación Productiva.

[4] The sectoral distribution was concentrated in three economic activities in 2015: 1) Agriculture, livestock, hunting and forestry (25%); 2) Manufacturing (10.6%); and 3) Trade (18.8%). Many Ecuadorian workers did not have social security at the time (53.9%), and only 20.2% of workers had higher education (18.6% university education and 1.6% non-university education).

[5] The urban unemployment rate (5.6%) was greater than the rural (2.9%) one.

[6] There is also a difference in this rate between urban and rural areas, since in rural areas 59.5% of workers are employed in the informal sector, while in urban areas this proportion reaches 31.3%.

[7] We did a simple regression between labor income and a dummy variable (0 = December 2015; 1 = December 2016). The coefficient is statistically significant and negative, which confirms the reduction in labor income for the whole country in December 2016.

[8] INEC: Instituto Ecuatoriano de Estadística y Censos.

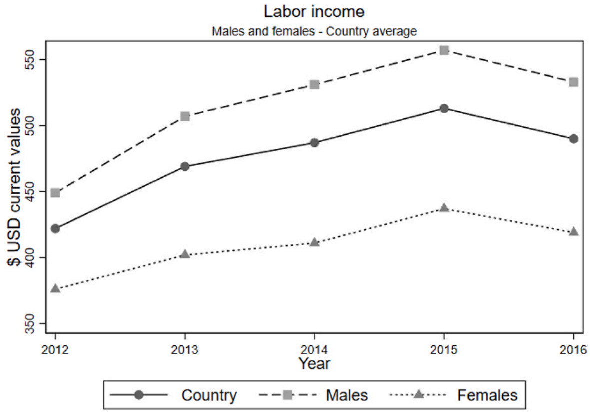

Fig. 1. Country Average Labor Income (USD, current values). Source: Cross section December ENEMDU (2012–2015). Own elaboration. Note: The estimated values were computed using the sample design.

respectively).

ENEMDU applies a rotary panel for collecting data using a 2-2-2 rotation scheme, as dwellings (25%) are substituted between quarters [49]. Following this scheme is possible to construct short-run individual-level panel datasets. In December 2015 and December 2016 the same individuals are followed up, which does not happen in other quarters and is the main reason we use a two period panel data set[9].

Our analytic dataset is composed by 102,128 observations (51,064 per year) and it represents 91% of the original ENEMDU data released by the INEC. We lost some information because we merged variables from different datasets: a) The cross section December 2015 and December 2016 ENEMDU (to compute schooling), b) The aggregate Ecuadorian Central Bank dataset of cantonal accounts (to compute specialization coefficients by canton), c) The aggregate Secretary of the Committee for Reconstruction and Productive Reactivation dataset (to add government allocations by canton), and d) USGS Shakemap data, in the next subsection we show how we calculated weighted average earthquake intensity measures: PGA, PGV, MMI, and its intensity quintiles.

Tables 1 and 2 summarize the variables used in our analysis.

4.1. *Intensity measures*

A crucial part of the approach we use in our empirical strategy is to quantify the earthquake impacts and find measures that fully capture the intensity of the earthquake and are not subject to arbitrariness in their definition. We use the USGS Shakemaps[10] as a source to calculate our geological measures. This is a crucial step to define which areas are considered affected by the earthquake in our models (treatment and control).

We choose to use Peak Ground Acceleration (PGA) as our standard measure of shock intensity, and for robustness we also use Modified Mercalli Intensity (MMI) and Peak Ground Velocity (PGV), as some studies suggest they might capture property and infrastructure damages in different ways [50]. By using multiples definitions of earthquake intensity, we are able to summarize most impacts correlated with the earthquake shock and build different treatment groups to test how wage distribution changes after the event. We merge the resulting Shakemaps with the political and administrative division of Ecuadorian municipalities (INEC shape) to build our dataset.

Then, we calculate the average measures for each geographical unit (canton) and divide the average cantonal values (PGA, MMI and PGV) into quintiles. The fifth quintile contains the most affected cantons, while the first one represents the least affected areas (we do the same for each one of the three measures). This process allows us to build different treatment groups and to relax the assumption that we need to define a fixed earthquake intensity in order for a canton to be considered affected or not[11]. Fig. 2 shows the Ecuadorian territory divided by earthquake intensity quintiles. Once all three measures are mapped, they resemble very closely how the hardest-hit provinces were defined by the Ecuadorian government.

[9] We still use the quarterly data as cross-sectional estimations for robustness.

[10] We use the latest update available to date (https://earthquake.usgs.gov/earthquakes/eventpage/us20005j32/shakemap/pga).

[11] The quintile classification between PGA and PGV coincides in 75%, PGA and MMI in 81%, and PGV and MMI in 79%.

[12] For PGV and MMI distribution maps, see Appendix 1.

[13] Ecuador has 224 cantons (Fig. 2), but in the clean database we used for our estimations there is information for individuals in 200 cantons, because the ENEMDU survey does not cover all of them. It is important to mention that when we merge ENEMDU panel database with other databases we lose some information too, for more details see Data and Methodology section.

Table 1
Continuous variables used in this study.

Data Panel: Continuous Variables					
Variable	Description	Unit	Level	Mean	N
Income	Monthly labor income	USD	Individual	470.9	55,076
Lnincome	Natural logarithm of monthly labor income	Ln	Individual	5.7	55,076
Schooling	Individual's years of schooling	Years	Individual	9.1	102,128
Government aid	Government fund allocation to cantons in the provinces of Manabí and Esmeraldas	Percent	Canton	0.3	102,128
Experience	Potential experience (age minus schooling minus six)	Years	Individual	26.0	102,121
Hours	Monthly worked hours	Hours	Individual	149.8	66,961
Lnhours	Natural logarithm of monthly worked hours	Ln	Individual	4.9	66,961
Specialization	Specialization coefficient	Number	Canton	0.3	102,128

*Dependent variable.
Source: INEC – data panel ENEMDU December 2015–December 2016.
Own elaboration.

Table 2
Binary variables used in this study.

Data Panel: Categorical Variables			
Variable	Description	Percent[a]	N
T	Treatment dummy (1 for individuals located in affected areas, 0 for individuals in control group)	83.5	102,128
	Treatment dummy (1 for individuals located in most affected areas, 0 for individuals in control group)	48.9	32,982
T	Time dummy (1 for December 2016, 0 for December 2015)	50.0	102,128
Urban	1 for urban, 0 for rural areas	59.5	102,128
Stability	1 permanent contract or other forms of job security, 0 otherwise.	21.5	68,842
Self	1 self-employment or employer	38.9	66,961
Informal	1 for workers in the informal sector	51.5	61,566
Sex	1 for males, 0 for females	48.2	102,128
Economic Activity	1 for individuals in agriculture, livestock, forestry and fishing	35.0	66,961
	1 for individuals in manufacturing	9.2	66,961
	1 for individuals in construction	6.2	66,961
	1 for individuals in wholesale and retail trade	16.0	66,961
	1 for individuals in transport and storage	5.2	66,961
	1 for individuals in hotels and restaurants	5.3	66,961
	1 for individuals in other activities	23.0	66,961

Source: INEC – data panel ENEMDU December 2015–December 2016.
Own elaboration.
[a] Percentage of observations equal to 1. All variables at the individual level.

5. Methodology

5.1. Empirical strategy

Our identification strategy relies on the fact that the 2016 Ecuadorian earthquake could be treated as a completely exogenous shock, which reduces the selection bias and produces adequate estimates [1]. argue that seismic activity is too ubiquitous across the country to make self-sorting feasible, even more if we consider that the last significant earthquake happened decades ago in another part of the country.

We combine matching (Coarsened Exact Matching, CEM), Quantile Regression (QR) and Difference in Difference (DID) techniques in order to check if there are heterogeneous effects linked to the earthquake along the labor income distribution. The rationale of choosing these methods is that our main research question about wage distributional changes requires longitudinal and individual data to be properly answered in an impact evaluation framework. To overcome some of the limitations of our 2-period main dataset we use different approaches to define the treatment and control groups, match the observations and estimate the earthquake effects across the wage distribution using different quantile regression and double difference strategies.

First, we perform a matching between sample observations using Coarsened Exact Matching (CEM) for both types of treatment groups (quintile 2 – quintile 5; quintile 5 only). Our observable characteristics for the matching process are years of schooling, household head (dummy), informal sector (dummy), economic activities[14], area (dummy) and sex (dummy). This allows us to reduce the imbalance in covariates between control and treatment groups.

After the matching process is done, we apply three sets of estimators: i. A quantile regression to estimate the changes in labor income (natural logarithmic difference), using workers' initial characteristics as explanatory variables; ii. A quantile difference in difference approach (QDID, [51], and iii. A quantile regression for panel data (QRPD, [52]. We will first discuss the simplest empirical

[14] i) Agriculture, livestock, forestry and fishing; ii) Manufacturing; iii) Construction; iv) Wholesale and retail trade; v) Transport and storage; vi) Hotels and restaurants; vii) Other activities.

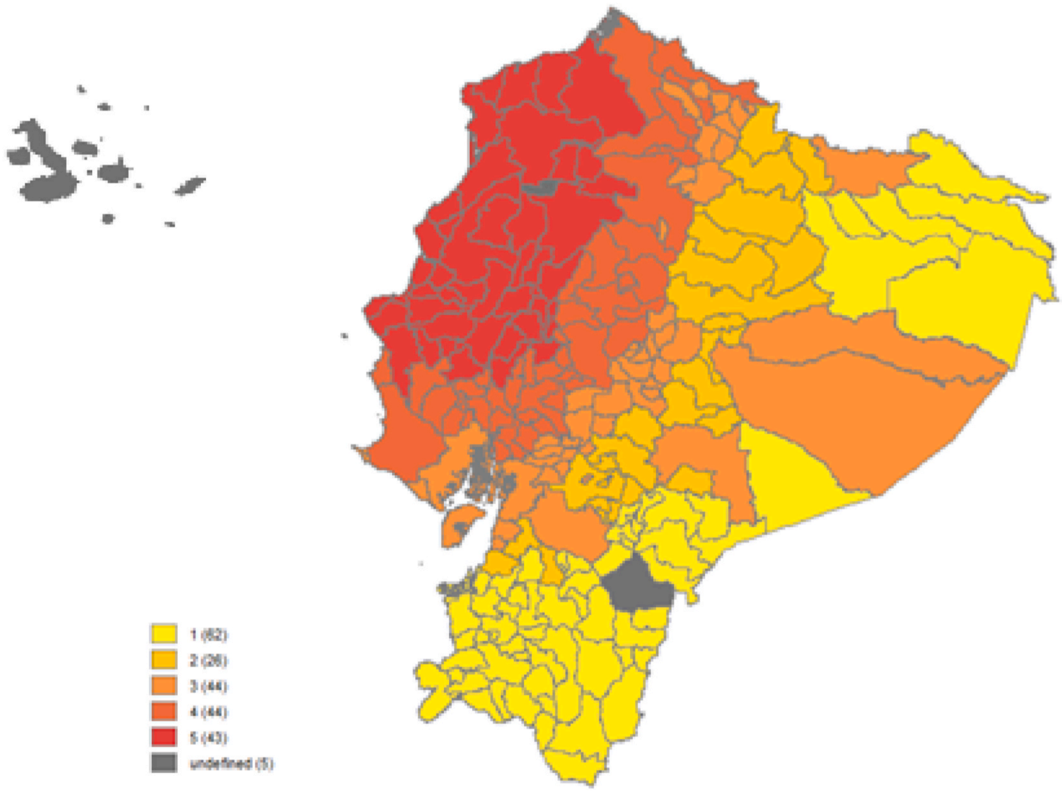

Fig. 2. Distribution of the average cantonal earthquake intensity (PGA quintiles)[12], [13]. Source: USGS, INEC. Own elaboration. NOTE: We did not include the Galapagos Islands in our analysis.

setting in which a standard quantile regression is applied, and then discuss the need for different estimators.

Following [2]; we estimate equation (1) in which the dependent variable is the difference between the natural logarithms of labor income (December 2016 minus December 2015). To deal with potential problems of endogeneity, our explanatory variables were the pre-earthquake characteristics (with the exception of the government aid and the specialization coefficient). Our variable of interest in this estimation is the dummy treatment (Ti).

$$\begin{aligned}(lnincomei,2016 - lnincomei,2015) &= \alpha + \beta_1(Ti) + \beta_2(government\_aid2018,c) + \beta_3(schoolingi,2015) + \beta_4(experiencei,2015)\\ &+\beta_5(experiencei,2015)^2 + \beta_6(urbani,2015) + \beta_7(stabilityi,2015) + \beta_8(lnhoursi,2015) + \beta_9(selfi,2015) + \beta_{10}(informali,2015) + \beta_{11,}\\ &{}_k(economic\_activityi,2015,k) + \beta_{12}(specialization2015,c) + \beta_{13}(sexi,2015) + \mu_{i,}\end{aligned} \tag{1}$$

Where the subindex i represents the individual and c represents the canton. *Lnincome*, is the natural logarithm of the monthly labor income (our output variable), T is the treatment binary variable, defined as 1 if the individual is located in seismic[15] areas and 0 otherwise.

Government aid, represents government fund allocation[16] to cantons in the provinces of *Manabí* and *Esmeraldas* expressed as percentages (December 2018). We assume that the allocation structure did not vary substantially over time. *Schooling*, corresponds to the individual's years of schooling and *Experience*, is the potential experience (age – schooling – six), we included the square of this term too.

Urban, is a dummy variable (1 for urban, 0 for rural areas), as well as *Stability*, a variable that takes the value of 1 if the individual has permanent contract or other forms of job security, 0 otherwise. Other binary variables include *Self*, to indicate whether individuals are either self-employed or owner-employers, as well as *Informal*, which takes the value of 1 for workers in the informal sector[17]. *Sex,* takes the value of 1 for males and 0 for females.

[15] First treatment definition (quintile 2 to quintile 5: PGA greater than 0.02 %g (m/s^2), PGV greater than 2.07 cm/s, MMI greater than 4. Second treatment definition (quintile 5): PGA greater than 0.145 %g (m/s^2), PGV greater than 15.84 cm/s, MMI greater than 6.3.

[16] Note that this variable is not at the individual level, but at the cantonal one. These are the assignments (monetary resources) executed in the cantons of the provinces of *Manabí* and *Esmeraldas* by government entities such as: Ministry of Transportation and Public Works (MTOP), Ministry of Urban Development and Housing (MIDUVI), Public Company for Strategic Development "Ecuador Estratégico" (EEEP), Public Banking, among others [53].

[17] Workers who belong to the informal sector are those who work in companies or establishments with less than a hundred employees and also these establishments/companies are not registered in the Ecuadorian Internal Revenue Service [1,54].

Economic activity is represented by the sub index *k*, which represents economic sectors[18], and *lnhours* accounts for the natural logarithm of the monthly worked hours. The specialization coefficient[19] is calculated for the year 2015 using the Ecuadorian Central Bank Cantonal Accounts. We choose this variable in order to control for the economic performance of the Ecuadorian cantons. Finally, μ represents the error term.

In order to better identify the quantile treatment effect, we perform two additional sets of estimations to overcome some difficulties that might arise when traditional difference-in-difference models are expanded to quantile estimations, mostly because the interpretation of the treatment effect is altered when fixed effects are present.

First, we use a quantile difference in differences approach (QDID) that is suitable for repeated cross section or short-panel data, which allows us to consider the complete counterfactual distribution of outcomes that the treatment group experienced in the absence of treatment, as well as the complete counterfactual for the control group as if they were treated [51]. The counterfactual distribution in QDID is computed "by adding the change over time at the qth quantile of the control group to the qth quantile of the first-period treatment group" [51]; p. 434). DID models are a special case of QDID, as the authors affirm that individuals are compared in their quantiles between groups and time. One of the disadvantages of QDID is that the estimator assumes that the distribution of unobservables should be the same in each subpopulation.

Equation (2) shows a typical DID implementation which takes the following form:

$$\begin{aligned}\text{lnincomeit} = {} & \alpha + \beta_1(\text{Ti x t}) + \beta_2(\text{t}) + \beta_3(\text{Ti}) + \beta_4(\text{government aid2018,c}) + \beta_5(\text{schoolingit}) + \beta_6(\text{experienceit}) \\ & + \beta_7(\text{experienceit})^2 + \beta_7(\text{urbanit}) + \beta_8(\text{stabilityit}) + \beta_9(\text{lnhoursit}) + \beta_{10}(\text{selfit}) + \beta_{11}(\text{informalit}) + \beta_{12,k}(\text{economic\_activityitk}) + \\ & \beta_{13}(\text{specialization2015,c}) + \beta_{14}(\text{sexit}) + \mu_{it}\end{aligned} \tag{2}$$

The time variable dummy is defined as *t* (1 for December 2016, 0 for December 2015). Our interest coefficient in this case is the interaction term (*Txt*), which shows the effect that could be attributed to the earthquake. We apply Equation (2) for each quantile of labor income.

We perform a third set of estimations applying the quantile regression for panel data (QRPD) developed by Ref. [52] in order to take into account the time dimension of our data set that the other estimators might not fully capture [52]. suggests a way to estimate distributional impacts (across outcome distribution) with an estimator that uses non-additive fixed effcts and observation-specific disturbance terms. QRPD helps us to relax some quantile regression identification assumptions, and it is important to mention that estimator is consistent even when we only have few years in the data set. The disadvantage of this estimator is that we are not able to adjust the standard errors by clustering or bootstrapping, as we do in the other two estimations. We estimate this QRPD specification using equation (2) as well.

5.2. Gender perspective and robustness checks

Since women tend to face higher opportunity costs to work outside their homes [56], they could be overrepresented in the informal sector [57] and have lower reserve salaries if they have suffered discrimination in the past [58]. We think that these are sufficient characteristics to justify estimating separate regressions for males and females in this study[20]. One limitation of this approach might be the potential selection biases that could arise because of different male and female participation rates. Though we acknowledge this issue as a possibility, we restrict our analysis towards women who are already in the labor market, as including job transitions would require more analysis than just performing a selection bias correction [18].

Yet the most important motivation to perform a gendered analysis is that cultural attitudes towards intra-household work in Ecuador are very prevalent, even for Latin-American standards [47]. Although the country is relatively egalitarian when it comes to shared property between males and females, intra-household attitudes are very important decision factors in disasters and other emergency situations, as the recent pandemic has shown [59]. If we observe different treatment coefficients for male or female workers in our empirical settings, it could be an indicator that these differences could be making their way towards employment and wage outcomes in the post-earthquake labor market.

5.3. Robustness checks

We also check the robustness of our estimates using all three measurements of earthquake intensity to define our treatment areas: Peak Ground Acceleration (PGA), Peak Ground Velocity (PGV) and Modified Mercalli Intensity (MMI). Both PGA and PGV are defined as instrumental intensities that measures ground shaking, according to Ref. [60] people tend to be more sensitive to ground acceleration than velocity, whereas structures might be more susceptible to velocity than acceleration [50]. MMI on the other hand combines instrumental measures with observed subjective intensities, which is then assigned a numerical scale [61]. In strict sense, the MMI is the only one that presents some degree of arbitrariness in its definition, yet it is still highly correlated with PGA and PGV. We

[18] i) Agriculture, livestock, forestry and fishing; ii) Manufacturing; iii) Construction; iv) Wholesale and retail trade; v) Transport and storage; vi) Hotels and restaurants; vii) Other activities.

[19] This variable is also at the cantonal level. This coefficient measures the degree of similarity of the regional economic structure (canton, gross added value) with the economic structure of the country [55]. A value close to 1 indicates regional specialization. Vij represents the value of gross value added in sector "i" of canton "j", its calculation formula is: $Q_r = 1/2^* \sum_i \left\{ ABS\left[\frac{V_{ij}}{\sum_i V_{ij}} - \frac{\sum_j V_{ij}}{\sum_i \sum_j V_{ij}} \right] \right\}$.

[20] We emphasize the estimation of separate regressions (excluding sex dummy variable) because it is reasonable to think that both groups have different reasons to offer their work in labor markets [56,58]; in other words, the determinants of the reserve salary could be gender-specific, and the assumption of homogeneous error terms for males and females could be challenged as well.

divided all of these measures in quintiles to construct slightly different treatment and control groups to check robustness.

Finally, it is important to mention that we estimate our models[21] using clustered standard errors, since the canton where the individuals are located defines the treatment status, thus allowing for possible correlations between individuals from the same canton. For the standard errors of QDID we use bootstrapping techniques as well. It is important to mention that we made these estimations only for matched individuals (common support), yet we also perform robustness checks using unmatched samples and a different matching technique as well (propensity score matching).

6. Results

6.1. Affected and unaffected areas

We present in Fig. 3 the evolution of labor income from December 2012 to December 2015 (pre-earthquake years) for the Esmeraldas and Manabí provinces[22] using ENEMDU cross-section surveys. To properly test the parallel trends assumption, we built an aggregate dataset for Ecuadorian provinces using 2012 to 2015 data using each wave's cross-sectional averages corrected by survey design weights[23]. We did not find differences between these coefficients, so the parallel trends assumption holds in this case study[24].

We define two treatment groups based on the earthquake intensity measures (PGA, MMI, PGV): i. workers located in the 2nd to 5th intensity quintiles, and ii. workers located in the 5th quintile. The control group is always the same, and consists of individuals located in areas with low (first quintile) or no affectation[25] (see Table 2).

In order to check descriptively whether labor markets of affected and unaffected zones had structural differences, we use the analytic panel dataset[26], and compute three widely used labor markets indicators: unemployment rate, percentage of people working in informal sector, and average monthly worked hours. These indicators were computed for two definitions of treatment groups: 1. workers in quintiles 2nd to 5th; 2. workers in the 5th quintile, as well as the control group. Table 3 shows that the unemployment rate of the control group in 2015 (3.8%) and in 2016 (3.5%) were smaller than the unemployment rate for both treatment groups (4.3% and 5.3% in 2015, 4.9% and 4.2% in 2016).

The informality rate in 2016 for control group was 49.2%, which was similar to the most affected areas (5th quintile). The average working hours were greater than the control group for the 2nd to 5th quintiles in 2016, but they were similar when compared to the 5th quintile.

Before presenting the results of our empirical strategy, we need to assess the differences between distributions in the treatment and control groups. For this purpose, we calculated the L1 statistic, which should be close to zero if both distributions are similar, so it is interpreted as a measure of global imbalance. We observe a good amount of global balance between both treatment groups, as our L1 statistic for the most seismic cantons (5th quintile) is 0.0619 (917 individuals were not matched) and our L1 statistic for the whole affected area (2nd to 5th quintiles) is 0.0335 (2677 individuals were not matched), so we can confidently proceed with our estimations[27].

6.2. Estimation results

We present first the estimations in which the workers located in the 2nd to 5th intensity quintiles are our treatment group (Table 4 and Table 5, males and females jointly and separately). Next, we present the estimations when workers located in the 5th quintile (most seismic regions) are defined as our treatment group (Table 6 and Table 7)[28]. The control group always stays the same, and consists of workers located in the first intensity quintile and in cantons without affectation. We report the treatment variable coefficient (equation (1)), and the interaction term (treatment and time for QDID and QRPD, equation (2)) for both PGA and MMI intensity measures[29].

The results presented in Tables 4 and 5 for males and females jointly are not entirely conclusive with respect to differentiated effects through the distribution of labor income, as positive and negative effects are seen throughout the distribution using the two intensity measures. If we focus our attention to the panel data estimates for quantile regression, it can be seen that standard errors are lower and the coefficients are greater in magnitude. We also performed estimations for both males and females separately and did not find a pattern with marked gender effects that was robust to all specifications and earthquake measures.

We must note that there is a considerable difference in the damage suffered by cantons at different earthquake intensity levels. For this reason, we also analyze what happens in the distribution of labor income of individuals located in the most affected cantons (fifth intensity quintile, a stricter definition of treatment group).

See Appendix 2 for complete regression results of this specification for males and females jointly. Complete results are available upon request.

[21] With the exception of QRPD, which uses Markov Chain Monte Carlo methods.

[22] 61% of the affected cantons were located in these provinces.

[23] Then we regressed the average wages and the dummy treatment, arguing that if the 2012 coefficient measures the difference between treatment (Manabí and Esmeraldas) and control is not statistically different to the 2013, 2014 and 2015 coefficients.

[24] We must note that the analytic sample does not allow this kind of flexibility, as the individual panel of 2015–2016 cannot be traced back to 2012.

[25] In the continental Ecuadorian territory, the cantons of Aguarico and Gualaquiza had no affectation, as well as the cantons of the Galapagos Islands, but the latter are not included in our analysis.

[26] We use our cleaned database of the individual data panel (December 2015–December 2016), see Data Section for details.

[27] We must note that our estimates were performed for matched individuals using the CEM output variable.

[28] Full regression results of all these estimations are available upon request. We present the complete results of the highest affectation for PGA treatments in Appendix 2.

[29] The PGV estimation is not presented here, yet its results will be still discussed here briefly and its details are available upon request.

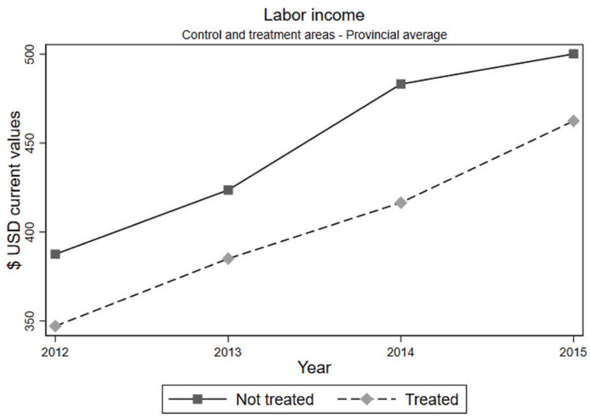

Fig. 3. Control group and treatment groups, average labor income (USD, current values). Source: Cross Section December ENEMDU (2012–2015). Own elaboration. Note: The estimated values were computed using survey design weights, provincial level.

Table 3
Labor Market Indicators: Affected and unaffected areas (December 2015 and December 2016, PGA).

Jointly affected areas (PGA quintile 2 - quintile 5)						
Year/Group	Unemployment rate		Rate of people working in informal sector		Mean Worked Hours (monthly)	
	Dec. 2015	Dec. 2016	Dec. 2015	Dec. 2016	Dec. 2015	Dec. 2016
Treatment	4.3%	4.9%	41.7%	44.4%	155.21	150.84
Control	3.8%	3.5%	48.2%	49.2%	152.39	144.57
Most affected areas (PGA quintile 5)						
Year/Group	**Unemployment rate**		**Rate of people working in informal sector**		**Mean Worked Hours (monthly)**	
	Dec. 2015	**Dec. 2016**	**Dec. 2015**	**Dec. 2016**	**Dec. 2015**	**Dec. 2016**
Treatment	5.3%	4.2%	46.6%	49.8%	149.51	144.95
Control	3.8%	3.5%	48.2%	49.2%	152.39	144.57

Source: ENEMDU cleaned panel data (December 2015–December 2016). Own elaboration.

Table 4
Treatment and interaction coefficient (treatment group defined as second to fifth intensity quintiles for PGA).

Peak Ground Acceleration (PGA, second to fifth quintile)									
Quantile	Quantile regression: Treatment coefficient.			Quantile difference in difference: interaction coefficient (QDID)			Quantile regression for panel data: interaction coefficient (QRPD)		
	Males and females	Males	Females	Males and females	Males	Females	Males and females	Males	Females
Q10	0.0873*	0.0888	0.0413	0.00313	−0.0113	−0.00241	0.0180	0.0406	0.181**
Q20	0.0540	0.0288	0.0773*	0.0108	0.0124	0.0126	0.0600***	0.117***	−0.174***
Q30	0.0191	0.0147	0.0323	0.0258	0.0209	0.0314	0.00323	−0.0548***	0.215
Q40	0.0240*	0.0107	0.0252	0.0290	0.0238	0.0448	0.00803	−0.0217***	0.0116
Q50	0.0200*	0.0128	0.0423*	0.0347	0.0216	0.0517	−0.0873***	−0.00970***	−0.0226
Q60	0.0169	0.00591	0.0296	0.0387*	0.0244	0.0396	0.0422***	−0.0446***	−0.188***
Q70	0.00183	−0.0125	0.0358*	0.0381*	0.0301	0.0351	0.0200***	0.0634***	−0.0597**
Q80	0.00201	−0.0147	0.0295	0.0325	0.0264	0.0375	0.0421***	0.0445	−0.0677**
Q90	0.00912	−0.0423	0.127***	0.0240	0.0148	0.0393	0.0746***	−0.0666***	−0.0611
N	19072	12799	6273	46483	29115	17368	46483	29115	17368

Estimates reported in Tables 6 and 7 show heterogeneous effects across the distribution for workers in the most seismic zones. There is a clear pattern in which the greater effects happen consistently in lower deciles. The effect of the earthquake, as it progresses through the distribution of labor income, decreases in magnitude or becomes statistically insignificant; in higher wage deciles it even turns negative. In the QDID[30] estimation for males and females (jointly), the first two deciles show positive effects[31] after the earthquake

[30] [51] mentioned that QDID compare individuals of treated and control groups, and compare individuals in time too, according to their quantile [52]. mentioned that the estimations using QRPD are interpreted as the "impact of the explanatory variables on the qth quantile of the outcome distribution".

[31] When the treatment intensity was defined by PGA, the first percentile workers located in more seismic zones saw increases in labor income of 10.9%, while the second percentile was 9.06%. For the case of MMI, the estimated effect of the earthquake is 11.8% and 9.48% for the first and second deciles respectively.

Table 5
Treatment and interaction coefficient (treatment group defined as second to fifth intensity quintiles for MMI).

Modified Mercalli Intensity (MMI, second to fifth quintile)									
Quantile	Quantile regression: Treatment coefficient.			Quantile difference in difference: interaction coefficient (QDID)			Quantile regression for panel data: interaction coefficient (QRPD)		
	Males and females	Males	Females	Males and females	Males	Females	Males and females	Males	Females
Q10	0.148[c]	0.135[b]	0.224[c]	−0.0162	−0.0333	0.00672	0.0193	−0.0565[a]	0.00142
Q20	0.0907[c]	0.0719[a]	0.133[c]	0.00905	0.00216	0.0328	0.173[c]	0.0281[a]	−0.0677
Q30	0.0294	0.0143	0.0578[a]	0.0294	0.0178	0.0513	−0.155[c]	0.00670	0.0111
Q40	0.0183	0.00327	0.0325	0.0333[a]	0.0196	0.0644[a]	0.0854[c]	0.0139[c]	0.0407[b]
Q50	0.0125	−0.000986	0.0407[a]	0.0407[b]	0.0184	0.0708[b]	0.0339	−0.0393[c]	0.0424
Q60	0.00132	−0.0102	0.0158	0.0426[b]	0.0193	0.0653[a]	0.0466[c]	0.0348	0.0332
Q70	−0.0200	−0.0384	0.0110	0.0429[b]	0.0245	0.0566[a]	0.0200[c]	0.0194[a]	−0.0926[b]
Q80	−0.0267	−0.0544[a]	0.0321	0.0366[a]	0.0213	0.0556	0.0470[c]	0.0115	0.0399[a]
Q90	−0.000413	−0.0841[b]	0.139[c]	0.0290	0.00464	0.0654[a]	0.0296[c]	0.0306	0.0188
N	18227	12267	5960	44473	27856	16617	44473	27856	16617

Source: ENEMDU cleaned panel data (December 2015–December 2016). Own elaboration.
[a] $p < 0.10$.
[b] $p < 0.05$.
[c] $p < 0.01$. PGV results available upon request.

Table 6
Treatment and interaction coefficient (treatment group defined as the fifth intensity quintile for PGA).

Peak Ground Acceleration (PGA, fifth quintile)									
Quantile	Quantile regression: Treatment coefficient.			Quantile difference in difference: interaction coefficient (QDID)			Quantile regression for panel data: interaction coefficient (QRPD)		
	Males and females	Males	Females	Males and females	Males	Females	Males and females	Males	Females
Q10	0.182[c]	0.151[c]	0.228[c]	0.109[a]	0.111[b]	0.139	0.137[c]	0.274[c]	0.172[a]
Q20	0.0949[c]	0.0898[b]	0.0895[a]	0.0906[b]	0.0915[b]	0.0763	0.113[c]	0.112[c]	0.192[b]
Q30	0.0509[a]	0.0551[a]	0.0239	0.0793[b]	0.0803[a]	0.0781	0.0448	0.0942[c]	0.104
Q40	0.0379	0.0417	0.0294	0.0758[a]	0.0698[a]	0.0872	0.0537[c]	0.0490[c]	−0.0625
Q50	0.0261	0.0232	0.0500	0.0756[b]	0.0690[a]	0.0889	0.131[c]	0.0738[c]	0.0880
Q60	0.0175	0.0117	0.0392	0.0646[a]	0.0604	0.0922	0.0394[c]	0.0187	−0.0280
Q70	−0.00486	−0.0154	0.0180	0.0812[b]	0.0547	0.105[a]	0.0258[b]	0.0600[c]	−0.0982[a]
Q80	−0.0151	−0.0241	−0.00904	0.0547	0.0250	0.0971[a]	−0.0666[c]	−0.0427[b]	0.0250
Q90	0.0120	−0.00222	0.0118	0.00883	0.0214	0.0138	0.0154	0.0266	−0.416[c]
N	6005	4281	1724	14708	9734	4974	14708	9734	4974

Source: ENEMDU cleaned panel data (December 2015–December 2016). Own elaboration.
[a] $p < 0.10$.
[b] $p < 0.05$.
[c] $p < 0.01$.

Table 7
Treatment and interaction coefficient (treatment group defined as the fifth intensity quintile for MMI).

Modified Mercalli Intensity (MMI, fifth quintile)									
Quantile	Quantile regression: Treatment coefficient.			Quantile difference in difference: interaction coefficient (QDID)			Quantile regression for panel data: interaction coefficient (QRPD)		
	Males and females	Males	Females	Males and females	Males	Females	Males and females	Males	Females
Q10	0.234[c]	0.141[b]	0.287[c]	0.118[b]	0.0995	0.147	0.0787[a]	0.181[b]	0.0305
Q20	0.131[c]	0.0832[a]	0.171[c]	0.0948[a]	0.0873[a]	0.107	0.0699[c]	0.145[c]	0.0896[a]
Q30	0.0567	0.0614	0.0968[b]	0.0875[a]	0.0668	0.110	0.0247	0.0229	−0.0980
Q40	0.0309	0.0152	0.0555	0.0888[b]	0.0710[a]	0.112	0.0752[c]	0.0784[c]	0.127[a]
Q50	0.0182	0.00642	0.0613[a]	0.0880[b]	0.0592	0.138[b]	0.0200	0.0273	0.0435
Q60	−0.0108	−0.0289	0.0182	0.0698[a]	0.0480	0.140[b]	0.0440[c]	0.0535[b]	0.0496
Q70	−0.0471[a]	−0.0702[b]	0.0103	0.0877[b]	0.0381	0.160[c]	0.0101	0.0335	−0.0572
Q80	−0.0547	−0.0905[b]	−0.0145	0.0643	0.0160	0.128[b]	0.0191	−0.0371	0.0303
Q90	−0.0141	−0.0392	−0.00244	0.0211	−0.0115	0.0803	0.122	−0.0351	0.186
N	4977	3602	1375	12253	8175	4078	12253	8175	4078

[a] $p < 0.10$.
[b] $p < 0.05$.
[c] $p < 0.01$. PGV results available upon request.

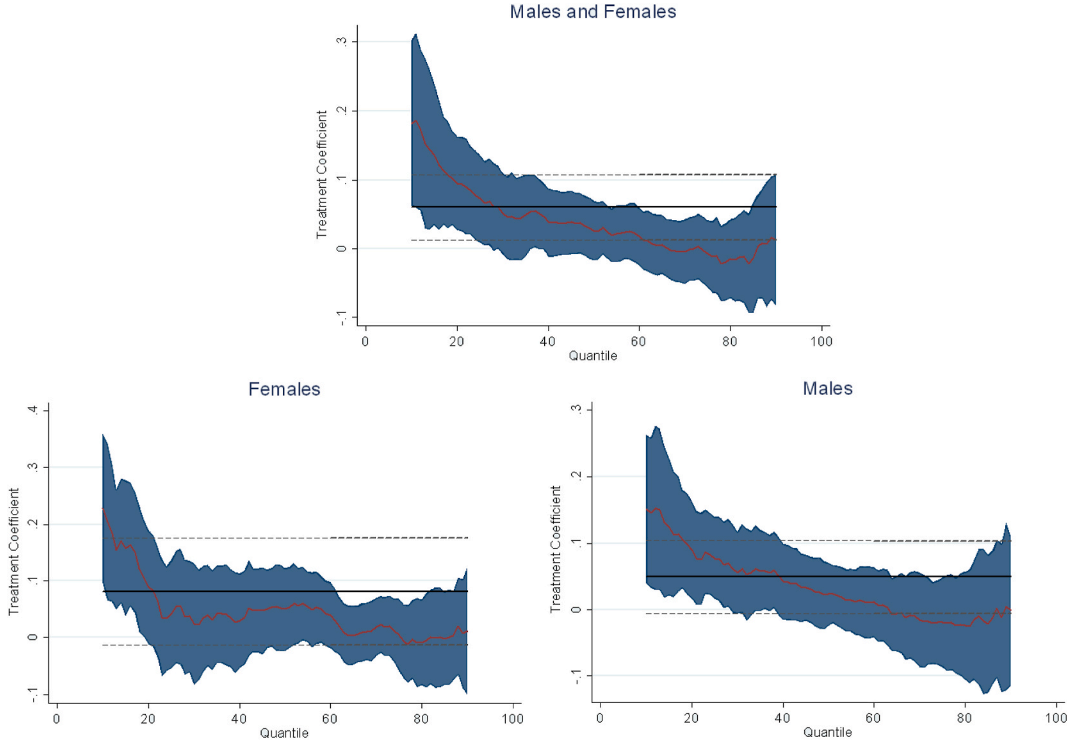

Fig. 4. Treatment effect coefficient for each percentile (equation (1), PGA estimation). Source: ENEMDU cleaned panel data (December 2015–December 2016). Own elaboration.

between 9% and 11%. We plot the estimates of equation (1) for each percentile in Fig. 4, where the first income percentiles show a positive effect (difference) associated to the earthquake. In the first decile, the labor income difference between 2015 and 2016 was 18.2%, while in the second decile it increased by 9.5% (using PGA as the earthquake measure).

6.3. Gender-specific models and robustness checks

The next question to answer is whether short-run reactions to the earthquake were similar using our gender-specific models. Estimates show higher standard errors across the income distribution for females than for males (QDID). Male workers located in the most seismic zones seem to have higher wage levels in the first quantiles due to the earthquake (QDID, PGA). However, coefficients for male and female workers lose significance for QDID in the MMI model. Although we do not see a clear gender difference pattern in the earthquake impact using models that measure levels (QRPD and QDID), the difference in coefficients for the quantile regression model that estimate changes [2] is consistently higher for females in all intensity measures. We interpret this as evidence that wages for female workers located in affected areas grew at higher rates compared to females in unaffected areas, and this rate was higher than the equivalent growth experienced by male workers.

We performed additional robustness checks: a. we estimate equation (1) replacing the binary treatment with the average cantonal PGA (continuous variable), b. we estimate equation (2) using QDID for the entire data set (without matching), c. we estimate equation (2) using QDID only using time, treatment and the interaction between both of them as independent variables, d. we use another matching specification and method, in which we apply a propensity score matching, and then estimate the QDID.

Table 8
Pooled estimation Time × Treatment interaction.

Quantile	Coefficient Txt
Q10	0.0888***
Q20	0.0817***
Q30	0.0615***
Q40	0.0490***
Q50	0.0366**
Q60	0.0369**
Q70	0.0389**
Q80	0.0175
Q90	−0.00288

Source: INEC-ENEMDU (cross-sectional quarterly surveys). Own ellaboration.

All the new estimated models reach the same conclusions as the estimates presented above, so we could indicate that our estimates are robust and the main conclusion holds: wage increases are found for this specific earthquake in the first quantiles of the distribution. The idea of these robustness checks was to ensure that our conclusions hold up when the empirical assumptions are challenged. Most notably, our 2-period estimations using individual level data would benefit from a more granular approach with respect to time periods.

As a final robustness check, we built a dataset using the quarterly surveys in a cross-sectional estimation to account for a shorter timeframe analysis. In this setup, December 2015 and March 2016 correspond to the pre-earthquake period, while June, September and December 2016 represent the post-earthquake period. This model was estimated for the PGA treatments using the highest affectation definition and a double-difference approach for repeated cross-sectional data. The time-treatment interaction coefficient was estimated using quantile regression and results are consistent with our previous estimation patterns (see Table 8), as the lower deciles show higher wage effects that decrease in magnitude and significance as we move to the higher percentiles.

7. Discussion

The cantons in our treatment group (5th quintile) are the areas in which social disruption, emergency responses, the destruction of dwellings and loss of productive infrastructure were higher. Government aid was especially present for these zones[32]. Even though we control for government allocations at the cantonal level, it might not be able to fully cover every single aspect of government and humanitarian aid, leaving out some tributary incentives for productive investment or exonerations related with international trade, capital movement taxes, or payment schemes for social security that could have contributed to the resilience of local labor markets of seismic zones as well [7].

We found a positive (and significant) wage variation attributable to the disaster for workers in most affected cantons, and this variation is stronger in the first quantiles of labor income distribution. Our results are aligned with the conclusions of [15]; who mention that poor people could diversify their sources of work earnings after a disaster event. In that sense, the positive effect observed in low wage quantiles could reduce inequalities, and this effect could be persistent in time given the right socioeconomic conditions. Another possible explanation for our findings is that the reconstruction period could have tipped these local labor markets to experience a positive outcome in wages and which made them resilient in the short run.

The gender differences in models measuring changes that do not show up in the QDID and QRPD models are important to interpret. The mechanism could be both tied to higher reserve salaries, but also to a lower salary base than males. In both cases, the post-disaster scenario could be affecting the decision process of when and how to join the labor market or look for better-paying jobs. On the one hand, intra-household inequalities could make this decision process harder for females, but on the other hand, labor supply constrains could be pushing wages up too.

We highlight the importance of a spatial disaggregated analysis, because if we had only observed the aggregate (country level) evolution of labor income, we could have concluded that apparently there was a decrease of the average monthly labor income in December 2016 (compared to December 2015), and incorrectly attribute that slump to the earthquake itself. Nevertheless, when we work with different levels of disaster intensity (PGA, PGV and MMI), define adequate treatment and control groups, and control our specifications for the effect of other variables, we are able to find a scenario with higher wages for workers in the lowest income percentiles associated to the 2016 Ecuadorian earthquake.

One of the possible explanations for the increase in labor income could be a surge in the demand for less educated workers (males and females). The earthquake did damage the local productive infrastructure and dwellings, some of which had to be rebuilt in the aftermath of the earthquake. Also, it is possible that companies had incentives to hire less educated workers in order to reduce their wage costs, even to the extent of replacing more educated workers with them. Thus, the post-disaster reconstruction process could have caused an increase in the demand for less educated workers in the earthquake-affected regions, producing an increase in the wages of these workers [12]. In the United States, both wage increases and decreases have been reported in the aftermath of climate disasters, depending on the scale and spatial distribution [62]. [2] reports a similar effect for agricultural workers after the Indonesian earthquake. Note that we implicitly assume that those workers located in the first percentiles of the salary distribution have lower qualifications, since labor income could be a good proxy of the worker's skills.

We have some evidence that this might have happened, as 23% of inactive workers in 2015 transitioned to a job in 2016, while only 17% of workers left the workforce in the same period in the most affected areas. This difference of 219 observations shows that more jobs were created than lost, yet the sectoral composition of the affected cantons did not significantly change after the earthquake. This transition was indeed observed in a significant percentage of the less-qualified workers (31% in affected areas) who took qualified jobs in the agricultural sector. Some of the less-qualified jobs were surely taken by workers who might have been previously out of the workforce, therefore giving further motivation to future researchers to dig deeper into job transitions and the quality of employment in the short and medium term.

Secondly, workers in the lower quintiles could be people who usually work in economic activities that demand workers with low skills or qualifications, and these economic activities are generally not highly productive [15]. mention that people who work in this type of activities, could diversify their sources of work earnings after a disaster, creating new opportunities for the poorest workers.

[32] 61% of the most affected cantons (5th quintile) belong to the provinces of *Manabí* and *Esmeraldas*. As we said in the Context section, the Value Added Tax (VAT) was increased by two percentage points for the entire country, with the exception of the provinces of Manabí and Esmeraldas, then those two extra percentage points were used for the reconstruction and economic reactivation of these provinces; similarly, targeted productive and tributary incentives were also given to these areas.

The evidence we observed in this case shows that the quality of employment was a probable explanation for the increase of wages in the lower quantiles.

It is also important to discuss some findings related to the covariates used in our empirical settings (see Table A3-3). The informality variable shows a negative and significant coefficient across quantiles. This could be explained by the predominant type of informality in Ecuador, more related to subsistence and the precarization of social benefits, effectively acting as a penalty of labor income [1]. Nevertheless, Table A3-1 shows positive signs for informality in the higher quantiles, which is explained by a higher increase in wages by 2016, but not necessarily higher income levels overall.

The variable describing self-employment and business ownership (self) shows a negative sign and could reflect that low-income self-employed are over-represented in our sample. We argue that this could be a reflection that self-employed individuals develop their economic activities in lower-productivity sectors where lower income is expected. In Table A3-1 we see positive values for higher quantiles, showing that labor income growth between 2015 and 2016 was higher for richer business-owners and self-employed individuals. Finally, the government aid variable calculated at the canton level did not show a statistically significant effect for all quantiles of income, as Table A3-3 shows that only the 50th to 80th percentiles present positive and significant values. This shows a heterogeneous effect of direct local government aid in labor income, meaning that not every worker benefited directly from direct aid. We should remark that this variable does not capture all the economic incentives, reconstruction, and relief measures provided by the government, and opens up possible research questions about efficiency in the public expenditure allocations after the earthquake.

8. Conclusions

In this study, we have found significant labor income distributional effects associated to the earthquake for the most affected locations and for the poorer income percentiles. A possible cause for these workers' increased labor income in the post-earthquake period might include government aid that went to the more affected areas, yet our findings indicate that not all workers had the same capacity to benefit from economic incentives. Our data does not capture direct transfers tied to the earthquake at household or community levels, as well as other kinds of national or regional incentives, but the effect on poorer individuals was robust to all our empirical specifications and earthquake measures for male and female workers.

We cannot rule out that part of the post-earthquake support policies might have found its way to increase the poorest workers' wages. The specific mechanisms of these changes are not completely clear in our analysis, as we also control for economic specialization (to consider regional economic performance), self-employment, local government investments, and informality[33]. We argue that the reconstruction economy incentives, broad public support to the affected regions and the re-orientation to more productive activities might explain why income shift patterns benefited the poorest workers. The varied tax and international trade incentives directed towards firms and individuals in the most affected areas could not be easily measured, yet they were very important in the aftermath of the earthquake [44,53]. This could be one of the explanations for the small effects we found in the cantonal direct aid variable coefficient.

We explore whether there is a gender-specific effect, as labor income increased at higher rates for females than males in the most affected areas, particularly in lower income percentiles. The Ecuadorian labor market has particular structural gender differences that we should not overlook in our discussion, as men are over-represented in employment participation and there is a persistent labor income gap between both sexes in favor of men, which also extends to intra-household dynamics [47]. Our results suggest that these changes could be explained both by higher reserve salaries, as well as constrained labor supply.

The wage prime for workers in highly affected areas, specifically for those who belong to the lower percentiles of labor income, represents a challenge for policy makers and researchers alike. There is still a need to unravel how the positive distributive effects could be sustained over time, and to design policies that improve the overall life conditions for the poorest workers struck by extreme events. Although our results suggest that public support might have made a difference in this specific disaster, the immediate question that arises for bigger/costlier disasters is whether government support will be enough or not.

The recent pandemic has highlighted the need to support workers in times of crisis [63], but only some rich countries have the means to provide universal assistance to workers and individuals at large when disasters are unfolded. In this case, the Ecuadorian society was able to support the most affected provinces, but it is not clear if the same would be achievable when the whole country experiences a crisis. More insights are needed to test the limits of public support, as it might not be uncommon for stable governments to feel overwhelmed by the magnitude of future emergencies. One policy implication that comes from our results is that government spending, economic incentives and aid flows should consider where and how to help vulnerable individuals. In this case, the most affected provinces were already vulnerable and the country efforts towards an inclusive reconstruction helped the lowest paid workers in this particular context.

Institutional weakness[34] surely affects the focalization of government aid destined to the most affected zones. In this context, resources might have been used in better and more efficient ways. Although we understand that focalization might be prudent for a country with limited resources such as Ecuador, we argue that good disaster governance, transparent aid distribution and strong institutions could make a big difference and allow for more universal policies that would effectively help the whole population in terms of crisis. Although Ecuador has not been immune to mismanagement and the possibility of localized corruption in the disbursement of

[33] In our estimations we do control for workers in the informal sector (dummy variable), although many definitions do exist. See Ref. [1] for further details.

[34] According to the Global Competitiveness Report (2019) Ecuador is ranked in 90th of 141 countries. Specifically, the institutional pillar weighs down the index and ranks the country in the 106th position.

aid, its institutions have survived bigger crisis, such as political turmoil and the recent pandemic. In the case of this particular earthquake, we believe that swift action and the economic incentives redirected to the provinces of *Manabí* and *Esmeraldas* helped to avert the immediate crisis and fast-tracked the reconstruction process. But Ecuador still remains a difficult place to invest and do business in, and stronger institutions could make bigger differences in future crises.

We also highlight the importance of policies that promote the inclusion of females in those new opportunities, and to identify existing and new gender gaps before they become normalized in the post-disaster work culture. The increase in wage rates could be seen as good news at first glance, but they could be a reflection of the difficulties female workers have to join the labor market. Gender-specific perspectives arise frequently in disaster research [3] and they should be considered in all stages of policy design, from diagnostics to final impact evaluations.

Similarly, future researchers could improve our understanding of how the quality of regional institutions affects the resilience of local labor markets to disasters [64]. finds that country vulnerability to disasters is lower for countries with better institutions and economic development, but a regional perspective could give valuable answers on the specific response tied to these places. Similarly, the role of social capital [22] and culture [31] might have been also overlooked as a source of resilience to disasters that needs to be considered in future research of labor markets.

There are also general policy recommendations made by other authors that are relevant for our discussion on the distributional effects we found [65]. indicate that policies developed for poverty and inequality need to consider disaster effects as well, since these events could quickly challenge how realistic the initial policy objectives are. Preparation and planning are necessary to face the consequences of disasters, thus governments (at national and local level) should consider possible responses to these types of shocks in their policy toolboxes [67]. Quick-response funds for disaster scenarios could be used to target known vulnerable groups such as female, informal and low-skilled workers in ways that are quicker, more transparent and less prone to overwhelm governments during the emergency itself.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1. Intensity quintiles for PGV and MMI

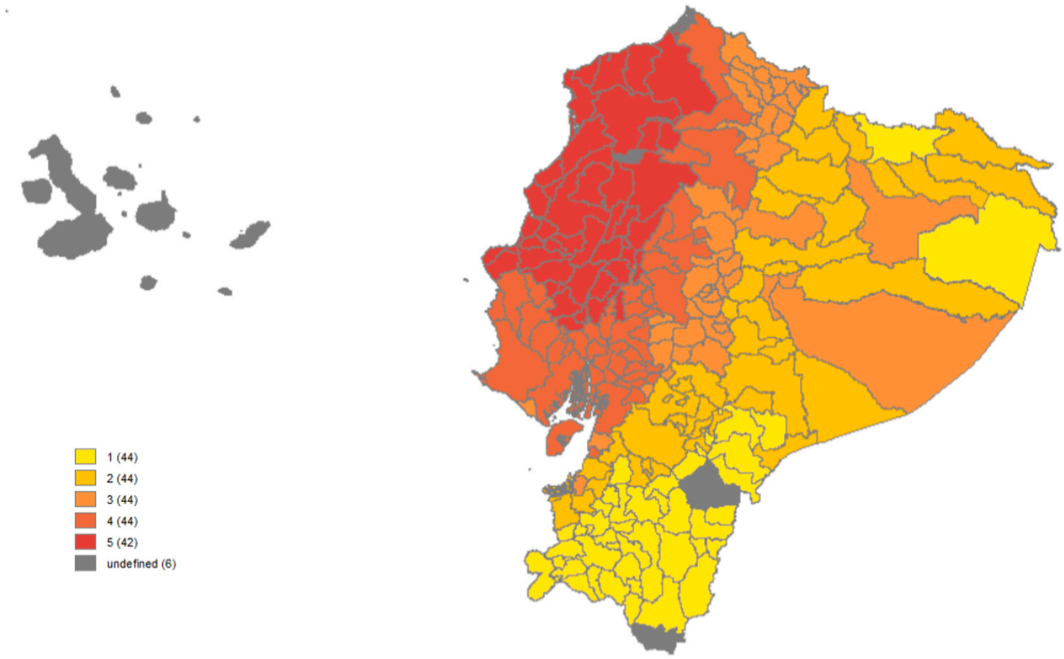

Fig. A1. Peak Ground Velocity (PGV). Source: USGS, INEC. Own elaboration.

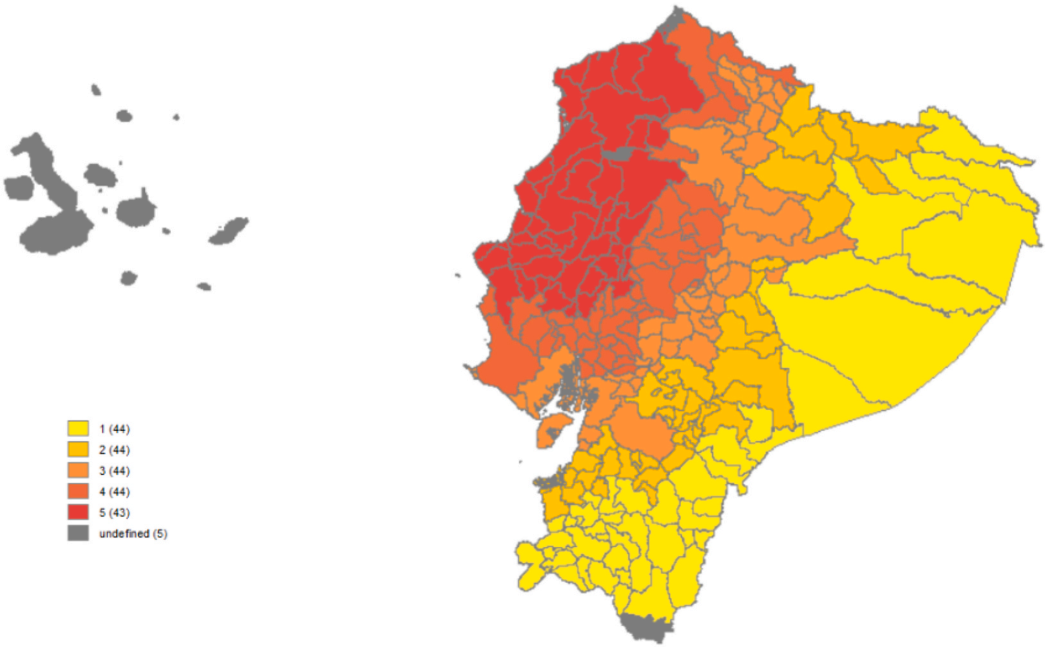

Fig. A2. Modified Mercalli Intensity (MMI). Source: USGS, INEC. Own elaboration.

Appendix 2. Complete output regressions

Table A3-1
Equation (1) PGA

Dependent variale: labor income natural logarithm difference	PGA								
	Q 10	Q 20	Q 30	Q 40	Q 50	Q 60	Q 70	Q 80	Q 90
Government aid	0.00452	0.0674	0.126	0.0759	0.174	0.228	0.360**	0.385**	−0.0228
SE	(0.260)	(0.250)	(0.212)	(0.259)	(0.247)	(0.185)	(0.148)	(0.155)	(0.236)
Schooling	−0.00220	−0.00417	−0.00320	−0.000201	−0.000373	0.00160	0.00361	0.00323	0.0114**
SE	(0.00550)	(0.00345)	(0.00211)	(0.00197)	(0.00214)	(0.00221)	(0.00250)	(0.00301)	(0.00551)
Experience	−0.00369	−0.00261	−0.00213	0.0000688	−0.000261	0.000473	−0.000617	0.000441	−0.00289
SE	(0.00417)	(0.00280)	(0.00207)	(0.00185)	(0.00153)	(0.00184)	(0.00194)	(0.00204)	(0.00339)
Experience 2	0.000000368	−0.0000234	−0.0000228	−0.0000449	−0.0000370	−0.0000446	−0.0000151	−0.0000194	0.0000675
SE	(0.0000640)	(0.0000481)	(0.0000360)	(0.0000338)	(0.0000284)	(0.0000344)	(0.0000379)	(0.0000391)	(0.0000626)
Urban	0.232***	0.0999**	0.0853***	0.0784***	0.0623***	0.0595***	0.0497*	0.0397	0.00339
SE	(0.0762)	(0.0462)	(0.0273)	(0.0227)	(0.0191)	(0.0226)	(0.0273)	(0.0323)	(0.0727)
Stability	0.258***	0.0706**	0.0314	0.00572	0.00461	−0.0135	−0.0375**	−0.0506**	−0.0927**
SE	(0.0749)	(0.0324)	(0.0246)	(0.0161)	(0.0163)	(0.0152)	(0.0182)	(0.0226)	(0.0448)
Lnhours	−0.0995	−0.166***	−0.186***	−0.185***	−0.259***	−0.260***	−0.280***	−0.318***	−0.354***
SE	(0.0717)	(0.0396)	(0.0280)	(0.0336)	(0.0315)	(0.0340)	(0.0272)	(0.0448)	(0.0550)
Self	−0.291***	−0.278***	−0.199***	−0.139***	−0.0213	0.0761**	0.204***	0.339***	0.537***
SE	(0.0638)	(0.0398)	(0.0360)	(0.0332)	(0.0329)	(0.0386)	(0.0302)	(0.0413)	(0.0602)
Informal	−0.0184	−0.0894**	−0.0454	0.0173	0.0493	0.0851**	0.109***	0.156***	0.231***
SE	(0.0559)	(0.0366)	(0.0322)	(0.0331)	(0.0323)	(0.0344)	(0.0310)	(0.0428)	(0.0605)
Agriculture	−0.00473	−0.124**	−0.0898**	−0.0300	−0.0227	−0.0209	0.0170	0.0174	0.0908
SE	(0.0574)	(0.0513)	(0.0358)	(0.0281)	(0.0251)	(0.0245)	(0.0312)	(0.0348)	(0.0896)

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Table A3-1 (*continued*)

Dependent variale: labor income natural logarithm difference	PGA								
	Q 10	Q 20	Q 30	Q 40	Q 50	Q 60	Q 70	Q 80	Q 90
Manufacturing	−0.106	−0.158***	−0.181***	−0.102**	−0.0518	−0.0419	−0.0398	−0.0277	0.00621
SE	(0.0739)	(0.0484)	(0.0481)	(0.0449)	(0.0495)	(0.0447)	(0.0444)	(0.0550)	(0.0758)
Construction	−0.0791	−0.0657	−0.0742*	−0.0490	−0.0560*	−0.0583	−0.0168	−0.0420	−0.0162
SE	(0.0901)	(0.0560)	(0.0400)	(0.0372)	(0.0339)	(0.0445)	(0.0410)	(0.0395)	(0.0717)
Wholesale and retail trade	−0.131**	−0.0997***	−0.0835***	−0.0471*	−0.0206	−0.00568	−0.0118	0.00630	0.0715
SE	(0.0637)	(0.0336)	(0.0236)	(0.0267)	(0.0221)	(0.0201)	(0.0251)	(0.0310)	(0.0503)
Transport and storage	−0.154	−0.125**	−0.122**	−0.0560	−0.0679**	−0.0617*	−0.0341	−0.0604	−0.0156
SE	(0.115)	(0.0497)	(0.0505)	(0.0370)	(0.0324)	(0.0339)	(0.0526)	(0.0480)	(0.0931)
Hotels and restaurants	−0.248***	−0.267***	−0.165**	−0.0352	−0.0322	−0.0136	−0.00766	−0.0135	0.0899
SE	(0.0940)	(0.0650)	(0.0673)	(0.0388)	(0.0320)	(0.0377)	(0.0426)	(0.0600)	(0.219)
Especialization	−0.178	−0.127	−0.0493	−0.0137	0.0201	0.0450	0.0717	0.0759	0.114
SE	(0.176)	(0.0992)	(0.0773)	(0.0719)	(0.0623)	(0.0637)	(0.0680)	(0.0859)	(0.124)
Sex	0.0533	0.0554**	0.0307	0.0332	0.0284	0.0420**	0.0542**	0.0599**	0.126***
SE	(0.0557)	(0.0277)	(0.0228)	(0.0223)	(0.0188)	(0.0181)	(0.0211)	(0.0255)	(0.0356)
Treatment	0.182***	0.0949***	0.0509*	0.0379	0.0261	0.0175	−0.00486	−0.0151	0.0120
SE	(0.0614)	(0.0350)	(0.0304)	(0.0255)	(0.0221)	(0.0213)	(0.0239)	(0.0291)	(0.0486)
_cons	−0.354	0.569***	0.831***	0.847***	1.293***	1.335***	1.501***	1.800***	2.077***
SE	(0.326)	(0.200)	(0.132)	(0.150)	(0.154)	(0.180)	(0.126)	(0.225)	(0.278)
N	6005	6005	6005	6005	6005	6005	6005	6005	6005

Source: ENEMDU cleaned panel data (December 2015–December 2016). Own elaboration. Note: Standard errors in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01.

Table A3-2
Equation (1) MMI

Dependent variale: labor income natural logarithm difference	MMI								
	Q 10	Q 20	Q 30	Q 40	Q 50	Q 60	Q 70	Q 80	Q 90
Government aid	0.0690	0.0977	0.151	0.143	0.292	0.354*	0.344**	0.386**	0.0934
SE	(0.299)	(0.290)	(0.308)	(0.286)	(0.261)	(0.198)	(0.162)	(0.185)	(0.233)
Schooling	−0.00396	−0.00756*	−0.00429	−0.00104	−0.00325	−0.00181	0.00328	0.00488	0.0106**
SE	(0.00714)	(0.00409)	(0.00293)	(0.00240)	(0.00228)	(0.00218)	(0.00238)	(0.00334)	(0.00536)
Experience	−0.00515	−0.00772**	−0.00402*	−0.00159	−0.00165	−0.000786	−0.000988	0.000487	−0.000771
SE	(0.00577)	(0.00328)	(0.00243)	(0.00184)	(0.00179)	(0.00209)	(0.00197)	(0.00222)	(0.00274)
Experience 2	0.0000374	0.0000792	0.0000217	0.000000833	−0.00000857	−0.0000184	−0.00000764	−0.0000193	0.0000327
SE	(0.0000834)	(0.0000545)	(0.0000403)	(0.0000314)	(0.0000314)	(0.0000379)	(0.0000350)	(0.0000431)	(0.0000453)
Urban	0.175*	0.111**	0.0851**	0.101***	0.0793***	0.0810***	0.0782***	0.0508	0.0503
SE	(0.0973)	(0.0523)	(0.0330)	(0.0231)	(0.0215)	(0.0241)	(0.0250)	(0.0311)	(0.0484)
Stability	0.235***	0.0872**	0.0335	0.00806	0.00155	−0.0292*	−0.0486***	−0.0591**	−0.115***
SE	(0.0840)	(0.0415)	(0.0291)	(0.0179)	(0.0171)	(0.0177)	(0.0179)	(0.0230)	(0.0363)
Lnhours	−0.118	−0.174***	−0.188***	−0.194***	−0.265***	−0.279***	−0.291***	−0.326***	−0.391***
SE	(0.0722)	(0.0462)	(0.0349)	(0.0378)	(0.0333)	(0.0401)	(0.0371)	(0.0551)	(0.0678)
Self	−0.294***	−0.247***	−0.178***	−0.118***	−0.00272	0.0893**	0.205***	0.319***	0.534***
SE	(0.0721)	(0.0396)	(0.0398)	(0.0376)	(0.0360)	(0.0433)	(0.0400)	(0.0525)	(0.0520)
Informal	−0.0482	−0.0766	−0.0579	0.0223	0.0365	0.0850**	0.123***	0.198***	0.264***
SE	(0.0656)	(0.0475)	(0.0446)	(0.0428)	(0.0379)	(0.0409)	(0.0340)	(0.0467)	(0.0469)
Agriculture	−0.0727	−0.150**	−0.0977	−0.0398	−0.0222	−0.0129	0.0699*	0.0899	0.150*
SE	(0.102)	(0.0718)	(0.0604)	(0.0475)	(0.0371)	(0.0371)	(0.0358)	(0.0574)	(0.0848)
Manufacturing	−0.0953	−0.144***	−0.133***	−0.0890**	−0.0510	−0.0447	−0.0513	−0.0200	−0.00599
SE	(0.0615)	(0.0466)	(0.0421)	(0.0374)	(0.0485)	(0.0411)	(0.0384)	(0.0548)	(0.0728)
Construction	−0.181	−0.105	−0.0944*	−0.0650	−0.0828**	−0.119**	−0.0742	−0.0364	−0.0524
SE	(0.138)	(0.0707)	(0.0562)	(0.0488)	(0.0397)	(0.0484)	(0.0590)	(0.0478)	(0.0677)
Wholesale and retail trade	−0.140**	−0.143***	−0.0801**	−0.0494	−0.0178	0.00000726	−0.00771	0.0420	0.0793
SE	(0.0675)	(0.0514)	(0.0330)	(0.0326)	(0.0272)	(0.0268)	(0.0332)	(0.0420)	(0.0620)
Transport and storage	−0.198*	−0.139**	−0.112**	−0.0604	−0.0482	−0.0508	−0.0611	−0.0515	−0.114*
SE	(0.116)	(0.0647)	(0.0492)	(0.0392)	(0.0398)	(0.0377)	(0.0526)	(0.0491)	(0.0666)
Hotels and restaurants	−0.259***	−0.290***	−0.129	−0.0224	−0.0379	−0.0232	−0.00412	0.0311	−0.0115
SE	(0.0824)	(0.0941)	(0.112)	(0.0533)	(0.0423)	(0.0360)	(0.0518)	(0.0540)	(0.0680)
Especialization	−0.0954	−0.0330	0.0264	0.0174	0.0147	0.00643	−0.0280	−0.0320	0.0120
SE	(0.214)	(0.149)	(0.138)	(0.105)	(0.0887)	(0.0749)	(0.0783)	(0.0945)	(0.132)
Sex	0.0831	0.0420	0.0433*	0.0380*	0.0312*	0.0364*	0.0572***	0.0627***	0.125***
SE	(0.0853)	(0.0287)	(0.0236)	(0.0224)	(0.0187)	(0.0195)	(0.0217)	(0.0220)	(0.0334)
Treatment	0.234***	0.131***	0.0567	0.0309	0.0182	−0.0108	−0.0471*	−0.0547	−0.0141
SE	(0.0622)	(0.0356)	(0.0385)	(0.0301)	(0.0249)	(0.0258)	(0.0249)	(0.0337)	(0.0378)

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Table A3-2 (*continued*)

Dependent variale: labor income natural logarithm difference	MMI								
	Q 10	Q 20	Q 30	Q 40	Q 50	Q 60	Q 70	Q 80	Q 90
_cons	−0.262	0.623**	0.819***	0.879***	1.365***	1.504***	1.609***	1.865***	2.267***
SE	(0.284)	(0.252)	(0.164)	(0.181)	(0.180)	(0.209)	(0.178)	(0.275)	(0.336)
N	4977	4977	4977	4977	4977	4977	4977	4977	4977

Source: ENEMDU cleaned panel data (December 2015–December 2016). Own elaboration. Note: Standard errors in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01.

Table A3-3
Equation (2) QRPD PGA

Dependent variale: labor income natural logarithm	PGA								
	Q 10	Q 20	Q 30	Q 40	Q 50	Q 60	Q 70	Q 80	Q 90
Txt	0.137***	0.113***	0.0448	0.0537***	0.131***	0.0394***	0.0258**	−0.0666***	0.0154
SE	(0.0431)	(0.0193)	(0.0331)	(0.0159)	(0.00882)	(0.0152)	(0.0131)	(0.0130)	(0.0422)
T	−0.00443	−0.0240	0.0721	0.0634***	−0.00678	−0.0125	0.00809	0.00345	−0.142***
SE	(0.0504)	(0.0158)	(0.0663)	(0.0186)	(0.00732)	(0.0100)	(0.0190)	(0.0125)	(0.0411)
T	0.0643**	0.0483***	0.0834***	0.0552***	0.0930***	0.00757	−0.0418	0.258***	0.151
SE	(0.0263)	(0.0171)	(0.0244)	(0.00763)	(0.0108)	(0.0104)	(0.0327)	(0.0240)	(0.112)
Government aid	−0.282	0.134	0.161	−0.389***	0.274***	0.667***	0.612***	0.400**	−0.246
SE	(0.218)	(0.135)	(0.140)	(0.0847)	(0.0496)	(0.114)	(0.201)	(0.182)	(0.213)
Schooling	0.0366***	0.0322***	0.0576***	0.0364***	0.0211***	0.00643***	0.0411***	0.0257***	0.0409***
SE	(0.00887)	(0.00303)	(0.00922)	(0.00129)	(0.00146)	(0.00180)	(0.00262)	(0.00370)	(0.00404)
Experience	0.0361***	0.0307***	0.0218***	0.0230***	0.0209***	0.0181***	0.0276***	0.0125***	0.0427***
SE	(0.0117)	(0.00117)	(0.00249)	(0.000426)	(0.000724)	(0.000387)	(0.00129)	(0.00196)	(0.0137)
Experience 2	−0.000515***	−0.000460***	−0.000186	−0.000317***	−0.000391***	−0.000445***	−0.000409***	−0.000190***	−0.000542***
SE	(0.000175)	(0.0000157)	(0.000117)	(0.00000517)	(0.00000835)	(0.00000734)	(0.0000270)	(0.0000264)	(0.000186)
Urban	0.193***	0.0792***	0.443*	0.0902***	0.116***	0.462***	0.0383**	0.144***	0.0264
SE	(0.0423)	(0.0142)	(0.235)	(0.00735)	(0.00620)	(0.0151)	(0.0162)	(0.0186)	(0.175)
Stability	0.137***	0.0508	0.168***	0.165***	0.146***	0.176***	0.0898***	0.0531***	0.116***
SE	(0.0487)	(0.0367)	(0.0214)	(0.00750)	(0.00956)	(0.00955)	(0.0132)	(0.0175)	(0.0293)
Lnhours	0.709***	0.643***	0.650***	0.599***	0.477***	0.541***	0.520***	0.373***	0.362***
SE	(0.0333)	(0.0490)	(0.0240)	(0.0105)	(0.00732)	(0.00850)	(0.0169)	(0.0199)	(0.0817)
Self	−0.617***	−0.535***	−0.482***	−0.359***	−0.356***	−0.290***	−0.220***	−0.114***	0.0844
SE	(0.0721)	(0.0289)	(0.0369)	(0.00579)	(0.0108)	(0.0212)	(0.0248)	(0.0223)	(0.120)
Informal	−0.438***	−0.395***	−0.304***	−0.376***	−0.150***	−0.0993***	−0.279***	−0.307***	−0.342***
SE	(0.0901)	(0.0230)	(0.0460)	(0.00474)	(0.0135)	(0.0120)	(0.0162)	(0.0206)	(0.0416)
Agriculture	−0.356***	−0.577***	−0.245***	−0.307***	−0.507***	−0.511***	−0.235***	−0.482***	−0.311***
SE	(0.134)	(0.0246)	(0.0509)	(0.0140)	(0.0157)	(0.0195)	(0.0253)	(0.0297)	(0.0643)
Manufacturing	−0.225**	−0.219**	−0.116	−0.319***	−0.473***	−0.439***	−0.349***	−0.509***	−0.321
SE	(0.110)	(0.102)	(0.140)	(0.0120)	(0.0156)	(0.0188)	(0.0213)	(0.0249)	(0.202)
Construction	−0.180	−0.267***	−0.124	−0.140***	−0.403***	−0.297***	−0.137***	−0.329***	−0.276***
SE	(0.163)	(0.0297)	(0.0810)	(0.0380)	(0.0208)	(0.0132)	(0.0345)	(0.0317)	(0.0589)
Wholesale and retail trade	−0.156***	−0.236***	−0.278***	−0.171***	−0.296***	−0.395***	−0.143***	−0.447***	−0.316**
SE	(0.0465)	(0.0333)	(0.0271)	(0.0200)	(0.0129)	(0.0215)	(0.0313)	(0.0192)	(0.149)
Transport and storage	0.0485	−0.0541	−0.103	−0.141***	−0.0236	−0.364***	−0.0521	−0.506***	−0.325***
SE	(0.0942)	(0.105)	(0.0868)	(0.0131)	(0.0156)	(0.0190)	(0.0319)	(0.0271)	(0.0531)
Hotels and restaurants	−0.441*	−0.156***	−0.468**	−0.0509***	0.0655***	−0.213***	−0.0629***	0.0918*	−0.389***
SE	(0.246)	(0.0244)	(0.209)	(0.0168)	(0.00976)	(0.0147)	(0.0244)	(0.0506)	(0.127)
Especialization	−0.636	−0.297***	0.607	−0.0299***	−0.0488***	−0.0490***	−0.204***	−0.0266	−1.294
SE	(0.416)	(0.0452)	(0.414)	(0.00712)	(0.00613)	(0.0141)	(0.0470)	(0.0372)	(1.001)
Sex	0.172**	0.306***	0.191***	0.298***	0.479***	0.459***	0.304***	0.431***	0.219*
SE	(0.0744)	(0.0223)	(0.0704)	(0.00872)	(0.0114)	(0.0113)	(0.0126)	(0.0260)	(0.115)
N	14708	14708	14708	14708	14708	14708	14708	14708	14708

Source: ENEMDU cleaned panel data (December 2015–December 2016). Own elaboration. Note: Standard errors in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01.

Table A3-4
Equation (2) QRPD MMI

Dependent variale: labor income natural logarithm	MMI								
	Q 10	Q 20	Q 30	Q 40	Q 50	Q 60	Q 70	Q 80	Q 90
Txt	0.0787*	0.0699***	0.0247	0.0752***	0.0200	0.0440***	0.0101	0.0191	0.122
SE	(0.0446)	(0.0185)	(0.0199)	(0.0233)	(0.0162)	(0.0112)	(0.0170)	(0.0456)	(0.0808)
T	0.270*	0.0788***	−0.0770*	0.0103	0.0203	0.0364***	−0.156***	0.0849***	−0.483***
SE	(0.155)	(0.0277)	(0.0456)	(0.0304)	(0.0576)	(0.0130)	(0.0388)	(0.0207)	(0.167)
T	0.0810*	0.128***	0.0987***	−0.0116	0.0707***	0.0883***	0.158***	0.113***	0.497***
SE	(0.0421)	(0.0213)	(0.0162)	(0.0231)	(0.0139)	(0.0214)	(0.0218)	(0.0178)	(0.174)
Government aid	−0.115	0.360*	0.160	−0.0777	0.427*	0.248***	−0.349***	0.0795	−0.558

(continued on next page)

Table A3-4 (*continued*)

Dependent variale: labor income natural logarithm	MMI								
	Q 10	Q 20	Q 30	Q 40	Q 50	Q 60	Q 70	Q 80	Q 90
SE	(0.255)	(0.204)	(0.123)	(0.169)	(0.225)	(0.0745)	(0.104)	(0.264)	(0.422)
Schooling	0.0549***	0.0415***	0.0442***	0.0373***	0.0446***	0.0361***	0.0491***	0.0517***	0.0343***
SE	(0.0105)	(0.00228)	(0.00316)	(0.00265)	(0.00124)	(0.00239)	(0.00105)	(0.00346)	(0.00643)
Experience	0.0263***	0.0154***	0.0342***	0.0202***	0.0260***	0.0167***	0.0235***	0.0191***	0.0363***
SE	(0.00731)	(0.00156)	(0.00940)	(0.00142)	(0.00114)	(0.00123)	(0.00137)	(0.00184)	(0.00602)
Experience 2	−0.000354***	−0.000181***	−0.000459***	−0.000262***	−0.000332***	−0.000251***	−0.000253***	−0.000175***	−0.000451***
SE	(0.0000875)	(0.0000194)	(0.000101)	(0.0000244)	(0.0000242)	(0.0000110)	(0.0000174)	(0.0000472)	(0.0000807)
Urban	0.138***	0.101***	0.0855***	0.227***	0.0288***	0.0977***	0.0134	0.148***	−0.191
SE	(0.0531)	(0.0164)	(0.0328)	(0.0197)	(0.00770)	(0.0111)	(0.0159)	(0.0237)	(0.133)
Stability	0.0683*	0.0707***	0.158***	0.107***	0.110***	0.116***	0.186***	0.118***	0.129***
SE	(0.0413)	(0.0272)	(0.0519)	(0.0202)	(0.0259)	(0.0119)	(0.0244)	(0.0293)	(0.0438)
Lnhours	0.696***	0.539***	0.620***	0.616***	0.633***	0.545***	0.319***	0.485***	0.417***
SE	(0.0393)	(0.0185)	(0.0472)	(0.0114)	(0.0116)	(0.0131)	(0.0209)	(0.0216)	(0.0475)
Self	−0.710***	−0.623***	−0.500***	−0.414***	−0.319***	−0.249***	−0.152***	0.00562	0.333***
SE	(0.0898)	(0.0367)	(0.0521)	(0.0261)	(0.0225)	(0.0171)	(0.0223)	(0.0383)	(0.0640)
SE	(0.127)	(0.0195)	(0.0236)	(0.0169)	(0.0267)	(0.0134)	(0.0292)	(0.0473)	(0.128)
Agriculture	−0.429***	−0.580***	−0.405***	−0.407***	−0.438***	−0.388***	−0.254***	−0.369***	−0.692***
SE	(0.0464)	(0.0455)	(0.0146)	(0.0193)	(0.0319)	(0.0120)	(0.0342)	(0.0421)	(0.148)
Manufacturing	−0.182**	−0.198***	−0.306***	−0.131**	−0.304***	−0.349***	−0.176***	−0.412***	−0.510***
SE	(0.0769)	(0.0145)	(0.106)	(0.0612)	(0.0391)	(0.0213)	(0.0284)	(0.0402)	(0.0608)
Construction	−0.248**	−0.283***	−0.143***	−0.277***	−0.166***	−0.269***	0.0900***	−0.178***	−0.190***
SE	(0.108)	(0.0342)	(0.0448)	(0.0380)	(0.0465)	(0.0373)	(0.0240)	(0.0247)	(0.0704)
Wholesale and retail trade	−0.125**	−0.315***	−0.222***	−0.134***	−0.222***	−0.201***	−0.113***	−0.206***	−0.324***
SE	(0.0577)	(0.0158)	(0.0590)	(0.0367)	(0.0169)	(0.0136)	(0.0427)	(0.0198)	(0.0804)
Transport and storage	−0.335**	−0.367***	−0.158*	−0.0625	−0.128***	−0.272***	−0.0957***	−0.351***	−0.00726
SE	(0.146)	(0.0571)	(0.0848)	(0.0903)	(0.0211)	(0.0232)	(0.0352)	(0.0358)	(0.158)
Hotels and restaurants	−0.380	−0.533***	−0.250***	−0.380***	−0.0994*	−0.0595***	0.283***	−0.0606	0.953**
SE	(0.317)	(0.0758)	(0.0293)	(0.0287)	(0.0566)	(0.0228)	(0.0918)	(0.0552)	(0.370)
Especialization	0.292	0.359***	−0.169	0.0335	−0.0198	0.0788***	−0.0493	0.475*	−1.281***
SE	(0.214)	(0.0750)	(0.237)	(0.0619)	(0.0344)	(0.0243)	(0.0490)	(0.287)	(0.308)
Sex	0.392***	0.343***	0.237***	0.292***	0.246***	0.342***	0.450***	0.371***	0.387***
SE	(0.0576)	(0.0242)	(0.0556)	(0.00993)	(0.0161)	(0.0154)	(0.0138)	(0.0229)	(0.0468)
N	12253	12253	12253	12253	12253	12253	12253	12253	12253

Source: ENEMDU cleaned panel data (December 2015–December 2016). Own elaboration. Note: Standard errors in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01.

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