Fernando González Vigil y Pilar Obando Hirano (editores)

17 DOCUMENTO DE INVESTIGACIÓN

Economía aplicada

Ensayos de investigación económica 2018

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Do large oil spills have effects on labor outcomes? The Peruvian case(*)

Carla Srebot Roeder
Yulia Valdivia Rivera

1. Introduction

A black elephant dwells in northern Peru and it is darkening the lives of people around it over time. In 1972, the Peruvian Government commissioned the state-owned oil company Petroperu to carry out the studies required for the construction of the Norperuano oil pipeline (Oleoducto Norperuano, ONP). Four decades later, the pipeline is synonymous with uncertainty. Limited maintenance work has triggered several oil spills throughout the Peruvian Amazon (Alayo, 2016). Indeed, the Environmental Assessment and Enforcement Agency (Organismo de Evaluación y Fiscalización Ambiental**,** OEFA) reported forty-two spills in fourteen districts during the period 2011– 2018.

The spills potentially affected as many as 526 thousand inhabitants across the five regions, twenty-three districts, and 2,037 settlements through which the ONP passes. These negative impacts may have been exacerbated by two main factors: (i) direct exposure to potentially contaminated natural resources in rural areas; and (ii) the high percentage of the economically active population who are engaged in farming and fishing in these regions.

Crude oil spills have severe consequences for health and welfare. For instance, after a spill into the community of Cuninico in 2014, the Ministry of Health found that 51% of the population exhibited urine mercury levels

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above the reference range, while 17% presented a urine cadmium level above the reference range (MINSA, 2016). High levels of mercury and cadmium severely increased the vulnerability of affected individuals to numerous diseases, such as diarrhea, allergic dermatitis, pharyngitis, and bronchitis (OEFA, 2016). In addition, 2,358 barrels of crude oil were spilled into the district of Urarinas in 2018, affecting 87,000m^2 of Amazonian soil and contaminating the river where inhabitants carry out their subsistence activities (e.g. fishing, hunting) (OEFA, 2016). In 2016, the OEFA reported that these spills affected more than 3 thousand people; caused losses of crops (cacao), flora, and fauna; and damaged farming infrastructure. Thus, not only has the local community become more vulnerable to certain diseases, but their incomes may also have been reduced due to their main economic resources being marred by the oil.

Because of the environmental wreckage caused by these spills, many of the affected individuals were forced to leave their home and relocate to new areas. However, relocation may not always be plausible given transaction and moving costs (Cameron & McConnaha, 2006). Therefore, several affected households had to remain in the damaged areas and bear the costs of contamination of their main resources and production factors. In some cases, this prompted the inhabitants who stayed to change economic activity as a risk-coping strategy.

In this paper we analyze whether oil spills from the ONP have had an impact on labor outcomes. We focus on the four largest spills that took place during the 2011–2017 period and examine their immediate effects—up to one year after the event occurred—on labor indicators. These include real hourly wage, share of population employed in traditional primary activities (i.e. farming, hunting, fishing), unemployment, adequate employment, visible underemployment, and invisible underemployment. These variables are relevant due to the potential impact of spills on health, life conditions, productivity, and displacement decisions. To address this research objective, we approach oil spills as a natural experiment: the measured treatment effects are driven by random failures in the ONP and not by the inhabitants of the treated or control areas. The empirical analysis is based on a difference-in-differences method, which is valid under the assumption that in the absence of the spill, the trend of labor outcomes between the treatment and control groups would have been the same.

Our main findings are that, since the occurrence of the four spills, individuals who live close to the affected areas earn 1.31 soles more per hour than individuals who reside farther away, and also are 3.19 percentage points less likely to continue working in the aforementioned traditional activities.

In addition, we analyze the possibility that the effects of oil spills may be heterogeneous along different levels of wealth.

We coincide with the findings of previous empirical studies, and add to this specialized literature by providing the first evidence about the impact that oil spills from the ONP have on labor outcomes, as well as revealing that oil spills generate a "recovery boom" in non-primary sectors. This is relevant because most of the existing literature has centered on the impact of spills on urban areas, overlooking the mechanism by which oil spills affect labor outcomes of people engaged in traditional rural activities. Given that individuals who reside in the regions that the ONP traverses are primarily employed in such activities, the implications of our findings may be a useful contribution to economic policy. In this sense, policies can be oriented to facilitating the relocation of affected individuals to those activities that are benefited by the boom, thus improving their labor income and well-being.

The remainder of this paper is organized as follows. In Section 2 we summarize the relevant literature on oil spills, natural disasters, and ensuing job displacement. In Section 3 we outline our theoretical framework. In Sections 4 and 5 we describe the data used and empirical strategy followed, respectively. In Section 6 we present the main results and robustness checks. Finally, in Section 7 we conclude.

2. Literature Review

The literature on the impact of oil spills has been motivated by the occurrence of several such events since the 1970s. The particularities of these events has allowed academics to use different empirical approaches as part of their research. With regard to the economic impact of oil spills, White and Molloy (2003) studied the following determinants of oil spill costs: type of oil, location, weather and sea conditions, quantity of oil spilled and rate of spillage, season of the year, and clean-up effectiveness. They found that such costs increase sharply if there are populated areas close to the spill. Hansen, Benson, and Hagen (2006) used a hedonic housing price methodology in which they took one mile as a sufficient distance to capture the perceived risk effect of rupture in the case of the Olympic Pipeline in Bellingham, Washington. They found that five years after the incident, proximity to the pipeline had a significant negative effect on house prices, and concluded that the mechanism at play was the increase of perceived risk as a consequence of the rupture. Previously, Cohen (1995) studied the economic losses that resulted from the Exxon Valdez oil spill, considering it a technological disaster (a combination of human error and mechanical malfunction). She found that the compensation paid by Exxon for economic injuries and for the employment of residents in clean-up efforts exceeded the economic losses caused by the spill's negative impact on fishing products. Similarly, Loureiro and Alló (2013) found that the extent of the oil spill had a significant positive effect on claims for damages and on the compensation received by the affected population, using OLS and Tobit methods in both cases.

As regards the impact of oil spills on labor market outcomes, empirical studies are rather scarce. One exception is Aldy (2014), who found that the Deepwater Horizon explosion in 2010 had a positive effect on employment and wages in the Gulf Coast region in the short run, based on a difference-in-differences approach. Aldy noted that the explosion caused a positive labor demand shock because of the clean-up efforts. This increased wages for local workers, including those who in-migrated because of the positive shock. But relevant guidance is also provided by academic literature on other adverse events, such as hurricanes, earthquakes, and droughts. Deryugina, Kawano, and Levitt (2014) studied the long-term economic impact of the Hurricane Katrina on its victims using evidence on individual tax returns. To define the counterfactual of the Katrina victims, they used the propensity score weighting technique to find comparable cities to New Orleans. Their results indicated a transitory negative impact on wages, employment, and household income that could be reverted after a few years. They concluded that dislocation is unlikely to be important for analyzing the costs of a negative event such as this. Groen and Polivka (2008) measured the effect of Hurricane Katrina on the labor outcomes of evacuees. While those who returned to their pre-Katrina areas had to cope with extensive damage to their homes and public infrastructure, those who did not return had to deal with unfamiliar labor markets and loss of their social networks. In particular, differences in housing damage explained approximately 63% of the difference in the unemployment rate between the two groups, in favor of those who did not return.

As for long-term effects, Carter, Little, Mogues and Negatu (2007) studied those of two natural disasters: the three-year drought of the late 1990s in Ethiopia and Hurricane Mitch in Honduras in 1998. Their study found that wealthy households were able to partially recover their pre-disaster level of assets, whereas the poorest experienced a longer period of deprivation and never recovered their previous level of capital. This led the authors to conclude that environmental shocks can be especially harrowing for those with lower income levels and can result in immediate increases in poverty. Along similar lines, Black, Arnell, Adger, Thomas and Geddes (2012) found that the poorest are more vulnerable to natural hazards and are also less able to be relocated. They suggested that in the face of extreme environmental events, the ability to relocate is correlated with "wealth," level of capital (financial, human, social), the availability of places to go, and fear of what would happen to property and assets left behind. Morrow-Jones and Morrow-Jones (1991) studied the recovery of movers who attribute their relocation to a natural disaster, proposing that temporary shocks became permanent for less-wealthy households due to decreased access to internal or external resources. In turn, Sawada and Shimizutani (2008) explained how natural hazards affect the income of those working in agriculture and related activities. Hazards, such as severe droughts and hurricanes, destroy crops and livestock, which are the sources of income for most farmers. These authors identified the two possible household risk-coping strategies as responses to natural disasters: (i) households change the quality and composition of expenditures by reducing unnecessary expenditures, or (ii) households use credit to smooth consumption. In either case, the existence of credit constraints has significant negative effects on risk-coping capacities among poor households.

Because of the high prevalence of household self-employment in Peruvian rural livelihoods, access to credit is limited (Laszlo, 2008). Therefore, the aforementioned risk coping strategies cannot be applied. This elucidates the potential constraints Peruvian rural households may have faced as a result of oil spills destroying natural resources and, in turn, their possible shifts to different economic activities. In the academic literature, this is known as job displacement. Kletzer (1998) stated that the reasons behind earnings losses due to job displacement are complex and involve theories of human capital and wage determination, given that losses of job-specific human capital and even permanent wage reduction are potentially implied. Moreover, the author proposed that because of the costs of displacement, displaced workers typically earn less in their post-displacement job than in their previous job. Likewise, workers who are reemployed in a different industry may have lower wages than those who regain employment in the same or similar industry.

In sum, the academic literature related to oil spills and their impact on labor market outcomes, which is primarily focused on urban areas, suggests that compensation for the affected population as well as remuneration for clean-up efforts exceed the negative effect of the adverse event. However, according to the academic literature on natural disasters, such events trigger higher rates of relocation and job displacement, respectively, in areas with a higher level of housing damage and high dependence on environmental resources. This explains the focus of our research. Because oil spills from the ONP have primarily affected populations in rural areas who generally base their income on natural resources and face credit constraints, we attempt to measure the impact of these oil spills on labor market outcomes and on inducing changes of economic activity. Since these effects on rural areas have not been studied before, our evidence makes an important contribution to the academic literature.

3. Analytical Framework

Oil spills, like other adverse events, differ in their economic impact. Populations of affected areas usually receive compensation and humanitarian aid in goods and chattels, and/or benefit from an increase in labor demand for clean-up efforts. As a result, households may experience a positive impact on their welfare. On the other hand, individuals affected by the loss of natural resources, public infrastructure, social networks, and household assets may suffer a negative impact on income and employment despite receiving compensation and aid. This gives rise to the following question: how do oil spills from the ONP impact the labor outcomes of the nearby population? In particular, three mechanisms are worth highlighting.

The first mechanism is related to the reduction in labor productivity due to an increase in vulnerability to diseases because of contamination of natural resources. The OEFA has reported that crude oil spills have caused extensive damage to nearby rivers, land, and field crops. Indeed, Peru's National Fisheries Health Agency (Organismo Nacional de Sanidad Pesquera, SANIPES) found that a vast number of fish had died in the Morona River after a spill, and that these fish were not suitable for human consumption due to their high levels of mercury and cadmium (Produce, 2016). Likewise, the contamination of two regionally important rivers (Pastaza and Utcubamba) and the National Reserve of Pacaya Samiria by a crude oil spill in 2013 severely increased the vulnerability of surrounding communities to several diseases, such as diarrhea, headaches, vomits, hives, allergic dermatitis, pharyngitis, bronchitis, and gastroenteritis (OEFA, 2016). This rise in diseases caused a decrease in working days and, consequently, in productivity, resulting in a negative impact on both the rate of employment and labor income.

The second mechanism relates to the reduced efficiency of production factors due to the deterioration of the ecosystem near the spills. Oil spills cause losses of fauna and flora in rivers and on land, as well as damage to farming infrastructure (OEFA, 2016). Furthermore, not only do oil spills destroy current agricultural and fishing production, but they also decrease crop yields, potential arable land, and fish growth rates. Thus, we can see how oil spills can potentially reduce the productivity of the production factors. This can bring about a decline in earnings as a result of large job losses in traditional agricultural and fishing activities.

The third mechanism is connected with increased job displacement caused by the deterioration of natural resources. This is because households near the ONP are reliant on these resources for most of their income; approximately 45% of the economically active population in the ONP regions are engaged in traditional fishing and agricultural work (INEI, 2017). This mechanism is reinforced by limited access to credit (Laszlo, 2008), which entails a paucity of risk-coping strategies (Carter et al., 2007). Oil spills significantly increase labor risk perception, which engenders changes of economic activity. In this regard, the level of destruction caused by spills to natural resources and production inputs determines whether or not workers change economic activity. Since oil leaks trigger extensive damage to natural resources and physical capital, workers in economic sectors that exhibit the greatest production losses may move to another activity as a risk-coping strategy. And because job displacement entails losses of job-specific human capital and a risk of lower wages (Kletzer, 1998), affected (displaced) farmers may also experience a decline in employment and earnings.

Although the academic literature suggests that job displacement can potentially have a negative effect on labor outcomes, the final result will depend on the income level of displaced individuals; indeed, the earnings of some individuals may increase after an oil spill. There are two possible explanations for this outcome. First, according to Chang, Stone, Demes, and Piscitelly (2014), after recovery from a natural disaster, the short-term increases in spending can create a "recovery boom" that benefits individuals who changed from the aforementioned traditional activities to others such as tourism and retail. Second, the earnings of the individuals affected by the spill could reflect positive relocation. That is, those who change sector can achieve income increases because the average wage in this new sector is higher than in the previous one. In northern Peru, wages received for non-primary activities are, on average, double those of primary activities (INEI, 2017).[1]

[1] This takes into account the income of workers from Cajamarca, Lambayeque, Piura, Amazonas and Loreto, following the methodology of the National Institute of Statistics and Informatics (Instituto Nacional de Estadística e Informática, INEI).

Furthermore, some communities within the areas affected by spills have received humanitarian aid, which may have had a positive impact on their welfare. In addition, Petroperú has hired local workers to clean up and decontaminate the areas affected by the spill. The company stated that it has paid 40 soles per day for cleaning up oil (Petroperú, n.d.). This has brought about a temporary increase in labor income, as well as a reduction in the unemployment rate among the affected population.

In the light of this pool of potential mechanisms and their negative or positive effects on labor outcomes, our hypothesis poses that the impact of the ONP oil spills on labor outcomes will be negative, and that their effect on changing economic activities will be positive. Therefore, we assume that given the magnitude of the spills, their negative impact on income and change of economic activity will have exceeded the effects of temporary job remuneration and humanitarian aid.

4. Data and Sample

Our empirical analysis combines data from the National Household Survey (Encuesta Nacional de Hogares, ENAHO), a nationally representative annual survey of household living conditions conducted by INEI, with data on oil spills from OEFA and the Supervisory Agency for Investment in Energy and Mining (Organismo Supervisor de la Inversión en Energía y Minería, OSINERGMIN). We focus on data covering the following regions through which the ONP passes: Piura, Cajamarca, Amazonas, Loreto, and Lambayeque. The outcome variables are all related to the labor market, the main one being labor income.

ENAHO contains measurable information on household demographic, social, economic, and geo-referenced (based on the latitude and longitude coordinates system) features. Our empirical analysis used this database of successive cross-sections from 2007 to 2017 . To quantify the impact of oil spills on labor outcomes, we take into account six dependent variables, also constructed from ENAHO: real hourly wage, share of population employed in traditional primary activities, unemployment rate, adequate employment, visible underemployment (or underemployment due to insufficient work hours) and invisible underemployment (or underemployment due to insufficient income). As control variables, we utilize socio-demographic and socio-economic characteristics both at individual and household levels and again sourced from ENAHO. We present the descriptive statistics of these variables in Table 1.

Table 1
Descriptive Statistics

	Mean		
	Treatment	Control	Difference
% Male	34.280	35.215	-0.934
	(0.544)	(1.473)	(1.445)
Average age	0.524	0.542	-0.017
	(0.016)	(0.006)	(0.016)
Average years of education	6.783	6.708	0.075
	(0.284)	(0.268)	(0.364)
Average hourly wage	4.308	4.699	-0.391
	(0.210)	(0.337)	(0.410)
% Unemployment	0.157	0.136	0.021
	(0.013)	(0.013)	(0.015)
% Farm activities	0.980	0.976	0.003
	(0.010)	(0.016)	(0.018)
% Born in district	0.831	0.774	0.057
	(0.038)	(0.097)	(0.095)
% Poor	0.385	0.354	0.032
	(0.036)	(0.023)	(0.036)
% Extreme poor	0.269	0.292	-0.023
	(0.054)	(0.065)	(0.089)
% Access to electricity	0.239	0.259	-0.020
	(0.076)	(0.113)	(0.122)
% Access to piped water	0.134	0.308	-0.174
	(0.037)	(0.120)	(0.125)
% Rural	0.160	0.194	-0.034
	(0.053)	(0.082)	(0.110)
Average number of household members	6.399	6.090	0.309
	(0.141)	(0.481)	(0.456)
Average number of income earners	2.258	2.344	-0.086
	(0.095)	(0.111)	(0.169)

Average distance to the closest spill	0.003	0.002	0.001
	(0.003)	(0.001)	(0.003)
% Mining	0.017	0.024	-0.007
	(0.005)	(0.013)	(0.013)
% Industry	0.013	0.012	0.002
	(0.004)	(0.004)	(0.006)
% Construction	0.052	0.065	-0.013
	(0.017)	(0.022)	(0.026)
% Commerce	0.007	0.005	0.001
	(0.002)	(0.002)	(0.003)
% Services	0.029	0.017	0.011
	(0.006)	(0.005)	(0.008)
% Health	0.019	0.015	0.003
	(0.008)	(0.006)	(0.010)
% Education	0.012	0.008	0.004
	(0.003)	(0.004)	(0.005)
% Public	36.527	94.284	-57.757
	(11.571)	(38.996)	(33.525)

Notes. *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. The mean and its standard error are clustered by district, taking into account an initial radius scale parameter of 400. Real monthly salary, poverty line, and extreme poverty line are measured in soles.

We used our second data source, from OEFA and OSINERGMIN, to create a database that includes the following information about oil spills that occurred between 2011 and 2016: location, number of spilled barrels, date, cause, and area affected in square meters. From this database, we restricted our study sample to the fourteen spills that were caused only by events attributable to ONP operational problems (such as corrosion, lack of maintenance, and repair failures), since spills triggered or caused by third parties could skew our results due to an endogeneity problem. In this sample, we focused on the four largest spills, which span a total affected area of at least 31,000 m^2, and, in order to define an impact radius centered at the exact location of the spills, we transformed the latitude and longitude location data used in ENAHO to the World Geodesic System 84 (WGS84). Because this conversion depends on the Global Positioning System (GPS) zone in which every household is located, we were able to calculate the geodesic distance from each household to each of the four oil spills.

To define the treatment group for each spill, we created an impact radius centered at the exact location of the spill that generates an area equivalent to the affected area in squared meters provided by the OEFA (2017) and OSINERGMIN (2017). Thus, the households located within this area formed part of the treatment group. A concern regarding this procedure is the size of the treatment groups, given the small area affected by these spills. For example, the spill that occurred in Morona, Loreto in 2016, had the largest affected area, with an impact radius of 1.26 kilometers. We addressed this problem by rescaling the impact radius of each spill by multiples of ten (from ten to 500). We consider this appropriate for two main reasons: (i) the area provided by the OEFA and OSINERGMIN is based on the number of spilled barrels and the direct impact of oil spills on natural resources and health; (ii) we are unable to determine whether the effect of spills on labor outcomes is restricted to households located within the directly affected area. Hence, the treatment group comprises all individuals whose households are located within these rescaled thresholds.

To define the control group, we also constructed a radius based on the affected area information taken from OEFA (2017) and OSINERGMIN (2017). For simplicity, we fixed the control area generated from this radius as equal in size to the area of the treatment group. Consequently, the control group is made up of those individuals who have not been affected by any spill and who dwell outside the treatment area, within an area of the same size as the treatment group.

The criterion for choosing the rescaled impact radius is the balance between covariate variables across the sample for the treatment definition. To ensure this balance, we take into account the number of individuals and the statistical comparison, between both the treatment and control groups. Table 1 above presents the treatment–control balance for an initial radius scale parameter of 400, which generates the most balanced sample. Only the average distance to the closest spill is statistically significant, which can be explained by the treatment definition itself and not by a systematic imbalance. These results suggest that the chosen radius guarantees the success of the treatment definition process, as both the treatment and control groups are statistically identical.

5. Empirical Strategy

Our strategy takes advantage of the fact that there were several oil spills in different locations along the ONP, at different times during the period 2011–2016. The identification strategy is a difference-in-differences procedure that uses the occurrence of oil spills as a treatment and compares individuals located close to spills to individuals farther away. The validity of this empirical strategy relies on the assumption that the effect of spills declines with distance, and that the evolution of outcomes in areas far and close to an oil spill location would have been similar in its absence.

For this identification strategy to be valid, we need the following three conditions to hold: (i) *Households within the treatment areas were indeed affected by the spill*. The plausibility of this condition relies on our use of pre-spill and post-spill data about the residents of affected and unaffected areas to control for economy-wide changes in the labor market before and after each event. (ii) *The measured treatment effects are driven by random failures in the ONP and not by the people in the treated or control areas.* To avoid a potential source of endogeneity, we only take into account crude oil spills that were caused by random breakdowns. (iii) *There was no selective spatial sorting across treatment areas*. This condition is plausible because, according to Petroperu, the pipeline is strategically located in northern Peru and its precise location is confidential. Thus, it can be assumed that if individuals decided to live near the pipeline, they did so without knowing its location before moving.

To estimate the effect of oil spills on labor outcomes (e.g. real hourly wage), we implemented a difference-in-differences strategy using regressions of the form:

$$(1) \qquad y_{ijt} = X_{ijt}\beta + \mu_j + \lambda_t + \gamma(Time_{jt} \times Treat_{ij}) + \varepsilon_{ijt}$$

where y_{ijt} is the labor indicator of individual i in area j in year t, with t ranging from 2011 to 2017; $Treat_{ij}$ distinguishes observations in the treatment group of area j from those in the control group of the same area; $Time_{jt}$ is a dummy equal to 1 if area j had an oil spill prior to year t; X_{ijt} is a set of time-varying controls at the level of individuals and "spills areas"; μ_j are "area" fixed effects and λ_t are year fixed effects. We also included district-specific time trends ρt to control for systematic trend differences between districts. This also controls for unobservable district-level factors evolving over time at a constant rate.

We also calculated the impact of oil spills on: (i) changes from the economic activity in which the individual was engaged before the spill (usually traditional farming, hunting, or fishing) to a different activity; (ii) unemployment rate; (iii) adequate employment rate; (iv) visible underemployment rate; and (v) invisible underemployment rate. For this purpose, we estimated the following linear probability model:

$$(2) \qquad m_{ij} = X_{ijt}\beta + \gamma(Time_{jt} \times Treat_{ij}) + \mu_j + \lambda_t + \rho t + \varepsilon_{ijt}$$

where m_{ij} is equal to 1 if individual i in area j (i) changed to another economic activity after the spill, (ii) was unemployed, (iii) was "adequately" employed, (iv) was a visible under-employee, or (v) was an invisible under-employee; respectively.

In the two previous regressions, the coefficient of interest is γ. It is interpreted as the causal effect of being affected by an oil spill. Our identifying assumption is that, conditional on area and time fixed effects and time-varying controls $X_{ijt},$ the occurrence of oil spills is orthogonal to the error term. To this end, we estimated regressions by clustering standard errors at district level, allowing for within-district serial correlation in the errors terms. We also tested for the presence of heterogenous effects on the impact of oil spills according to socioeconomic status and estimate the following interacted specification:

$$(3) \qquad m_{ij} = X_{ijt}\beta + \gamma(Time_{jt} \times Treat_{ij}) + \textstyle\sum_2^5 \omega_k(Time_{jt} \times Treat_{ij} \times Wealth_{kijt}) + \mu_j + \lambda_t + \rho t + \varepsilon_{ijt}$$

where $Wealth_{kijt}$ takes a value equal to one if the individual belongs to the "k" wealth quintile. The ω coefficients were estimated relative to the lowest wealth quintile—the omitted coefficient. For instance, the case $k = 2$ denotes the effect of oil spills on the labor outcomes of individuals in the second wealth quintile relative to the first one.

The key identifying assumption of the difference-in-differences estimator is that the outcome variable trends would have been the same in both groups (treatment and control) in the absence of spills. To investigate whether there are no differential trends between both groups, we estimated the following equation by allowing for leads and lags of the treatment:

$$(4) \qquad y_{ijt} = \beta_0 + \textstyle\sum_{k=-3}^{1} \vartheta_k(\tau_{jt} = k) + X_{ijt}\beta + \mu_j + \lambda_t + \rho t + \varepsilon_{ijt}$$

where τ_{jt} takes a value equal to one when an observation is k years away from the year the spill took place. The case $\tau = 0$ denotes the immediate year after the occurrence of the spill. Note that k equal to −3 or 1 denotes, respectively, more than three years before or one year after the spill's occurrence. A test of the differences-in-differences assumption is $\vartheta_k = 0 \ \forall \ k < 0$; i.e. the coefficients on all lags of the treatment should be zero. This implies that there are no significant differences in the outcome variable trends of treatment and control groups. We balanced the event study by including events in the data that occurred at least seven full years in the pre-spill period and one year in the post-spill period.

6. Analysis of Results

In this section, we report the main empirical results and discuss them in the light of the analytical framework explained in Section 3. Oil spills act as labor demand and supply shocks to the local economy and generate two effects. First, an increase in departure from primary farming and fishing activities driven by the massive destruction of their major input: natural resources. Second, spills can create a "recovery boom" that benefits certain economic sectors (e.g. health, mining, and services) and workers displaced from the aforementioned primary activities (Chang, Stone, Demes, & Piscitelly, 2014). The latter may lead to an increase in real wages or the employment rate.

Event study analysis illustrates the basic idea behind the identification strategy. Appendix Figures A.1.1 to A.1.6 show the results for the event study, indicating that there is no evidence of pre-existing trend differences in the labor outcomes (considering an initial radius scale parameter ranging of 400). The estimates in specification (4) are not statistically different from zero in the years before the spill occurred. Thus, the counterfactual trend behavior of the treatment and control groups are statistically the same and support the causal interpretation of the treatment effect on real hourly wage, participation in primary farming and fishing activities, and the unemployment rate.

Accordingly, the estimates indicate that oil spills lead to an increase in real hourly wages and a decrease in the share of population employed in primary farming and fishing activities. The results indicate that, *ceteris paribus*, a person living in an area in which an oil spill occurs is six percentage points less likely to work in the primary farming or fishing sector one year after the spill. The estimates also reveal that one year after the event, *ceteris paribus*, people located nearer to a spill location earn 2.83 additional soles per hour than the population farther away.

6.1 Effects Of Oil Spills On Labor Outcomes

Table 2 shows the main empirical results of our estimations under the difference-in-differences approach. In this table, we estimate Model (1) and Model (2) as linear probability models and cluster the standard errors by district. We also apply clustering by primary sampling unit (conglomerate) to allow for arbitrary autocorrelation within the cluster over time, and we find that our standard errors are smaller. Next, we report the more conservative standard errors—i.e. those clustered by districts. And Table 2 also reports the estimates of γ, the parameter associated with the interaction of treatment and time variables—i.e. with the impact of spills.

Impact on real wages

Column 1 of Table 2 presents the estimate of the real hourly wage. To control for the fact that oil spills may be correlated with characteristics associated with higher income (e.g. whether the household is located in an area with access to drinking water and electricity), we include time-varying controls plus district and year fixed effects. The coefficient, which gauges the effect of oil spills (γ), is positive and significant at the five percent level. This suggests that oil spills are associated with an increase in real hourly wages for individuals close to its location, relative to individuals farther away.

Under the assumption that the evolution of real hourly wage in locations far from and close to a spill location would have been similar in its absence, we can interpret these results as evidence of a positive effect of oil spills on labor income. The magnitude of the effect is economically significant: *ceteris paribus*, an individual living in an area close to a spill location earns 1.31 soles more per hour than an individual who resides farther away, after the spill's occurrence.

Table 2
Impact of Oil Spills on Labor Outcomes

	Hourly wage	Share of population employed in primary farming and fishing	Unemployment	Adequate employment	Visible underemployment	Invisible underemployment
	(1)	(2)	(3)	(4)	(5)	(6)
Spills	**1.3145****	**-0.0319****	0.0072	**0.1010****	-0.0163	**-0.09163***
	(0.5000)	**(0.0141)**	(0.0108)	**(0.0363)**	(0.0192)	**(0.0413)**
Mean of Dep. Var. (before)	4.2871	0.9764	0.1458	0.2049	0.0740	0.7130
R^2	0.1420	0.1927	0.0418	0.1607	0.0608	0.1179
Number of districts	10	11	11	11	11	11
Number of individuals	1,701	3,100	1,757	1,757	1,757	1,757
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Spill fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes. *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Regressions include an initial radius scale parameter of 400. Standard errors are clustered at district level. All regressions include year and spill fixed effects. The full set of control variables at individual level includes: age, indicator for male gender, marital status (equal to one if the individual is married or cohabiting), number of years of education. Household controls include: number of household members, number of household income earners, indicator for household access to piped water, dummy for household access to electricity, and dummy for urban residence.

Impact on the employment rate in the farming and fishing sector

Column 2 of Table 2 contains the estimation results for the employment rate in the primary farming and fishing sector. We estimated model (2) as a linear probability model. As expected, the estimate of γ is negative and significant at the five percent level, suggesting that oil spills lead to a decrease in the probability of working in the farming and fishing sector in areas close to the spills, relative to areas farther away. *Ceteris paribus*, an individual living in an area close to the spill location is 3.19 percentage points less likely to work in the said sector after the occurrence of the spill. While the economic magnitude of the coefficients in the real hourly wage and the share of population employed in these traditional activities is not inconsiderable, we find no effect on the invisible underemployment rate (see column 6 of Table 2).

Next, we analyzed the possibility that the effects of oil spills may be *heterogeneous* along levels of wealth. In Table 3, we introduce interaction terms between spill impact (time variable multiplied by treatment) and the dummies of wealth quintiles (2-5). In all cases, we find that, after the spills, individuals living in wealthier households earn higher hourly wages and are less likely to work in the traditional farming and fishing sector than individuals in poorer households (who belong to the first wealth quintile—the omitted coefficient). For individuals in the second and third wealth quintiles, the estimates show that people located close to spills earn 3.26 soles and 3.04 soles more per hour, respectively, than those farther away in households in the first wealth quintile. The coefficient of the triple interaction is not statistically significant for the fourth and fifth wealth quintiles. As regards the likelihood of working in farming and fishing, column 2 of Table 3 shows that individuals with greater exposure to oil spills in wealthier households are less likely to work in said activities. The results are significant for the second, third, and fifth wealth quintiles. We find that living close to oil spill locations decreases the likelihood of working in these traditional activities by 56.8 percentage points for individuals in the wealthiest quintile, relative to the first one.

Table 3
Heterogeneous Effects by Levels of Wealth

	Hourly wage	Share of population employed in primary farming and fishing	Unemployment	Adequate employment	Visible underemployment	Invisible underemployment
	(1)	(2)	(3)	(4)	(5)	(6)
Spills	-0.6434	0.0338	0.0031	-0.001	-0.0340	-0.0160
	(0.3955)	(0.0275)	(0.0177)	(0.0388)	(0.0330)	(0.0405)
Spills x Second wealth quintile	**3.2592****	**-0.0789***	-0.0266	0.0250	0.0574	-0.0659
	(1.0887)	**(0.0424)**	(0.0238)	(0.1188)	(0.0323)	(0.1045)
Spills x Third wealth quintile	**3.0410***	-0.0390	**0.0339***	0.1070	-0.0179	-0.1613
	(1.4703)	(0.0296)	**(0.0158)**	(0.1019)	(0.0563)	(0.1124)
Spills x Fourth wealth quintile	1.7829	**-0.1671***	-0.0020	-0.0472	**0.0654****	-0.0286
	(1.7391)	**(0.0857)**	(0.0179)	(0.1186)	**(0.0268)**	(0.1249)
Spills x Fifth wealth quintile	0.3105	**-0.5680****	**-0.0729****	**0.2140***	-0.0564	-0.0757
	(5.3340)	**(0.1928)**	**(0.0298)**	**(0.1015)**	(0.0710)	(0.1123)
Second wealth quintile	2.1995***	-0.0320**	0.0042	0.2462***	-0.0019	-0.2102***
	(0.2976)	(0.0143)	(0.0081)	(0.0260)	(0.0279)	(0.0486)
Third wealth quintile	3.8910***	-0.0295***	-0.0033	0.5266***	-0.0255	-0.3920***
	(0.3790)	(0.0089)	(0.0055)	(0.0232)	(0.0324)	(0.0510)
Fourth wealth quintile	6.3405***	-0.1132**	-0.0212*	0.7595***	-0.0439*	-0.5554***
	(0.7963)	(0.0423)	(0.0099)	(0.0473)	(0.0212)	(0.0568)

Fifth wealth quintile	11.3205***	-0.0646	-0.0266	0.8874***	-0.1128***	-0.6169***
	(1.1581)	(0.1018)	(0.0154)	(0.0390)	(0.0297)	(0.0457)
R^2	0.3035	0.2764	0.0552	0.3932	0.0705	0.2890
Number of districts	11	11	11	11	11	11
Number of individuals	1,701	2,794	1,757	1,757	1,757	1,757
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Spill fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes. *** $p<0.01$, ** $p<0.05$, * $p<0.1$**.** Standard errors in parentheses. Regressions include an initial radius scale parameter of 400. Standard errors are clustered at district level. All regressions include year and spill fixed effects. The full set of control variables at individual level includes: age, indicator for male gender, marital status (equal to one if the individual is married or cohabiting), number of years of education. Household controls include: number of household members, number of household income earners, indicator for household access to piped water, dummy for household access to electricity, dummy for urban residence, and indicators of wealth quintile of the household (second wealth quintile, third wealth quintile, fourth wealth quintile, fifth wealth quintile, base: first wealth quintile).

Possible Mechanisms

We have shown that ONP oil spills are associated with an increase in real labor income and a reduction in traditional farming and fishing employment in areas closer to the events. Here, we present two possible explanations for these results. First, as mentioned in Section 3, when an oil spill from the ONP takes place, Petroperu is the company responsible for the clean-up and decontamination operation. To this end, the company hires local workers from the affected districts and pays them 40 soles per day to clean up crude oil, for a period that depends on the number of spilled barrels. This oil-cleaning period, in the case of the spills we include in our sample—the four largest, from 2011 to 2016—has been at least three months on average. Thus, local workers hired as oil cleaners in treated areas received an income boost of 40 soles per day for at least three months after the spill.

Second, oil spills entail large losses in farming and fishing production, as mentioned in Section 3. This extensive damage to natural resources and physical capital generated a change from these forms of primary production to more productive sectors with higher wages. In this context, it is worth mentioning that natural disasters can create a recovery boom in non-primary sectors, which benefits displaced workers (Chang et al., 2014). The expanded labor demand increases wages in the affected areas, which may also explain why individuals close to spills experience an increase in their labor income in comparison to those farther away. We analyze the plausibility of this explanation by estimating Model (2) on employment rate by different sectors. The results of the estimated coefficient (γ) is shown in Table 4. The coefficients for the mining and services sectors are positive and significant at the one percent level. The estimates in the table show that, *ceteris paribus*, an oil spill increases the likelihood of working in services by 1.31 percent points and in mining by 0.72 percent points in areas close to the spills, relative to areas farther away. Hence, oil spills trigger a change from the farming and fishing sector and a relocation of work to the services and mining sector.

Table 4
The effect of Oil Spills in Employment by Sectors

	Sector								
	Farm	Mining	Industry	Commerce	Construction	Services	Health	Education	Public
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Spills	**-0.0319****	**0.0072*****	0.0110	0.0197	0.0190	**0.0131*****	0.0065	-0.0073	0.0080
	(0.0141)	**(0.0022)**	(0.0140)	(0.0205)	(0.0143)	**(0.0041)**	(0.0144)	(0.0144)	(0.0074)
Mean of Dep. Var. (before)	0.9764	0.0027	0.0232	0.0605	0.0141	0.0068	0.0227	0.0182	0.0068
R^2	0.1927	0.0142	0.0492	0.0996	0.0369	0.0253	0.064	0.1263	0.0445
Number of districts	11	11	11	11	11	11	11	11	11
Number of individuals	3,100	3,100	3,100	3,100	3,100	3,100	3,100	3,100	3,100
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spill fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Regressions include an initial radius scale parameter of 400. Standard errors are clustered at district level. All regressions include year and spill fixed effects. The full set of control variables at individual level includes: age, indicator for male gender, marital status (equal to one if the individual is married or cohabiting), number years of education. Household controls include: number of household members, number of household income earners, indicator for household access to piped water, dummy for household access to electricity, and dummy for urban residence.

6.2 Robustness Checks

To test the robustness of our results, we varied our definition of treatment by changing the initial radius scale parameter. Appendix Figures A.2.1 to A.2.6 show the effects of the estimates of oil spills considering an initial radius scale parameter ranging from 350 to 500. It is important to note that the coefficient of γ keeps its sign and significance level when taking into account a radius close to 400 (390 or 410) which, as mentioned in Section 4, contains the most balanced sample. To the extent that the scale parameter is more distant from 400, the estimates of γ differ more from what we find in Section 6.1. This is not surprising, as the treatment and control regions are less similar because the samples are not as balanced as with a scale parameter of 400.

- **Selective Migration**

Migration is a foremost concern in our study because our sample is based on successive cross-sections and we cannot identify migrants, and so the observed increase in real hourly wages and the reduction in the farming and fishing employment rate may only be reflecting compositional changes in the labor force. Following Aragon and Rud (2013), we address this concern indirectly by evaluating whether or not oils spills have led to changes in the observable characteristics of the labor force in areas closer and farther from the spill's location. To this end, we focus on different measures of human capital. The indicators include: years of education, primary school completion, the individual's sex, and whether the individual was born in the district. In all cases, we estimated the baseline regression (1) with spill and year fixed effects as the only control variables. Table 5 shows the results. These address concerns about whether the increase in real hourly wages and the reduction in the farm employment rate are driven by migration of more productive workers or the out-migration of farmers to other regions.

Table 5
Changes to Characteristics of Labor Force

	Age	% Male	Years of Education	% Complete Primary	% Born in district
	(1)	(2)	(3)	(4)	(5)
Spills	-1.1054	0.0353	0.7769	0.0531	-0.0697
	(1.2936)	(0.0272)	(0.6379)	(0.0564)	(0.0523)
R^2	0.0182	0.0026	0.0190	0.0159	0.0990
Number of districts	11	11	11	11	11
Number of individuals	3,642	3,642	3,634	3,634	3,642
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Spill fixed effect	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No

Notes. *** p<0.01, ** p<0.05, * p<0.1**.** Standard errors in parentheses. Regressions include an initial radius scale parameter of 400. Standard errors are clustered at district level. All regressions include year and spill fixed effects.

- **Placebo Tests: Randomization of Dates**

The key identification assumption underlying our approach is that oil spills in northern Peru arose from random failures of the ONP. We have made use of the exact timing of oil spills to verify that changes in labor outcomes occur after the occurrence of a spill in an area, not before it. Moreover, in order to check that the effects found are not spurious, we have also estimated Model (1) using placebo oil spill dates. Specifically, we tested for the potential impact of placebo (fake) dates for spills in the treated areas. Using a uniform distribution, for each spill, we randomly chose ten dates from the year before a spill's occurrence. The time indicator ($Time_{jt}$) of Model (1) is defined according to the placebo dates. That is, it takes value equal to one starting from the placebo date for spill j, or zero otherwise. Then, we estimated the same specification of Model (1) for each of the ten placebo dates. The results are displayed in Appendix Figures A.3.1 to A.3.6. These show that the coefficient of γ is not statistically different from zero, thus indicating that with placebo dates the oil spills have no significant effects.

7. Summary and Conclusions

Our empirical analysis finds that, after controlling for time-varying controls and for time-invariant district characteristics, oil spills lead to significantly higher hourly wage and a lower employment rate in traditional farming and fishing activities. These effects are stronger for individuals of higher socioeconomic status, as measured by household wealth. Furthermore, our analysis by economic sectors indicates that oil spills trigger a “boom recovery” in other activities such as services and mining, which expands their labor demand. This explains the mechanism behind the increase in wages and the reduction of employment in traditional farming and fishing.

To test the main assumption behind the empirical differences-in-differences strategy, we implement an event study analysis, which allows us to interpret the aforementioned results as the causal effect of how oil spills impact labor outcomes in northern Peru. Notably, our findings are quite robust. In fact, when we test for both the potential impact of placebo dates of oil spills in treated areas as well as of selective migration, we find no statistically significant effect, which further supports our main results and proves that these are not simply spurious correlations.

We believe that the implications of our findings will serve as a useful contribution to economic policy—not only because they provide strong evidence that can help settle the debate on the impact of oil spills on labor outcomes, but more importantly because they address concerns about who truly benefits from the boom recovery following an oil spill. Our findings emphasize that the poorer are more vulnerable to oil spills, as they face higher capital constraints and cannot relocate or move easily to an economic activity other than primary farming and fishing. Furthermore, as oil spills have represented a major social and economic concern since the increase in their frequency, we believe that our results can be useful not only in revealing the magnitude of the impact of spills but also, because of our geo-referenced research strategy, in helping policymakers to identify the affected population and implement effective post-event policies. In this sense, policies can be oriented to reassigning affected individuals to those activities that benefit from the boom, thus offering greater returns on work.

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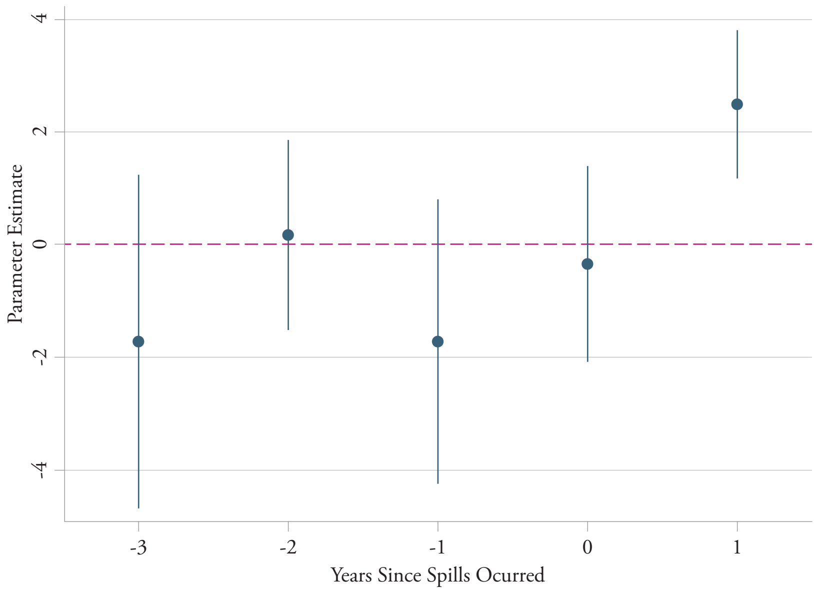
Appendixes

A.1. Event Studies[2]

Figure A.1.1.
Event Study on Real Monthly Salary



[2] Event study graphs shows parameter estimates in years before and after spills occurred from a regression that controls for year and spill fixed effects, as well as time-varying covariates at individual and spill level. Regressions include an initial radius scale parameter of 400. Whiskers indicate 95% confidence interval. Standard errors are clustered by district.

Figure A.1.2.
Event Study on Employment Rate in
Farming Activities

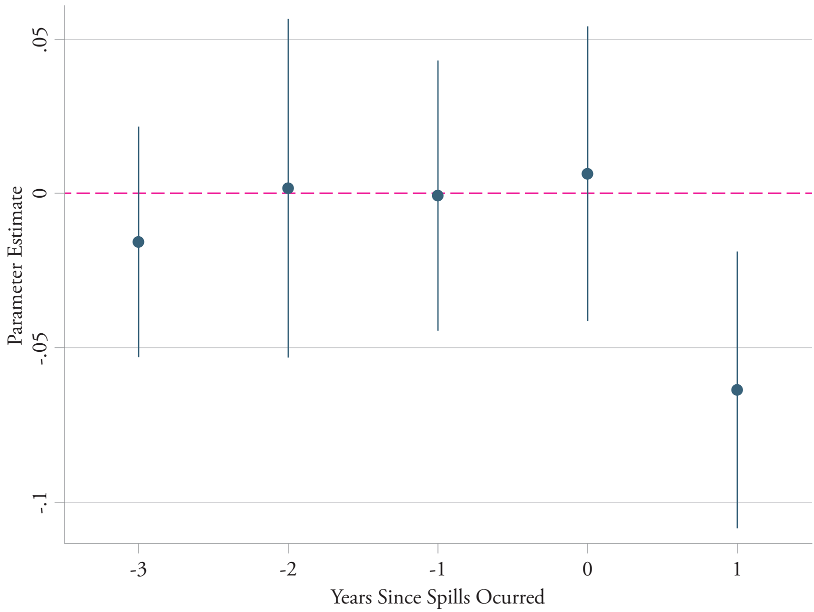


Figure A.1.3.
Event Study on Unemployment Rate

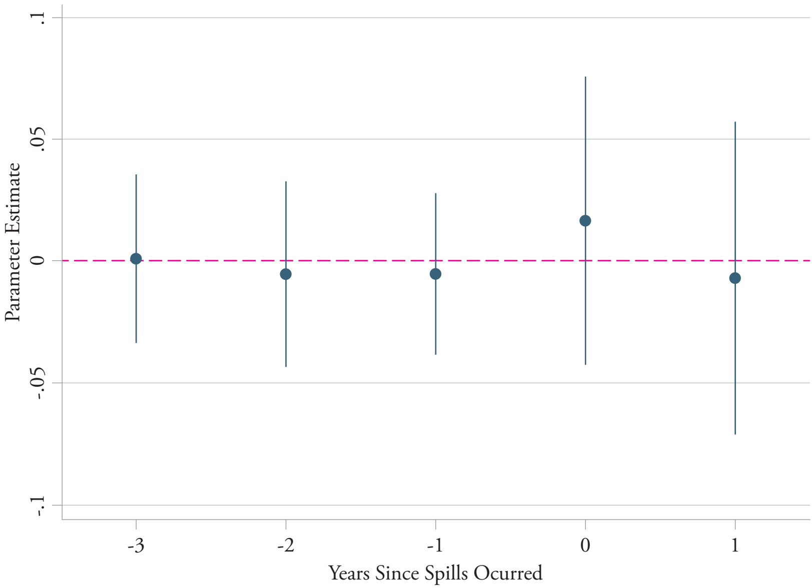


Figure A.1.4.
Event Study on Adequate Employment Rate

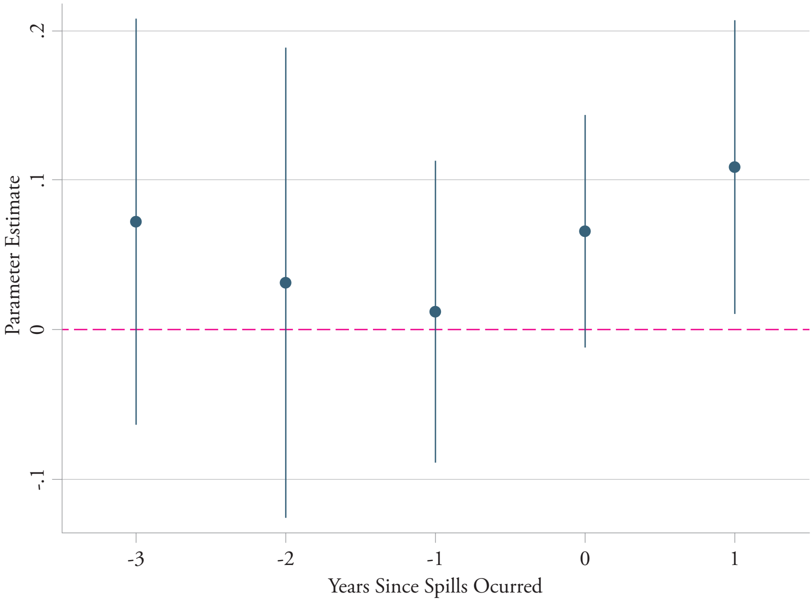


Figure A.1.5.
Event Study on Visible Underemployment Rate

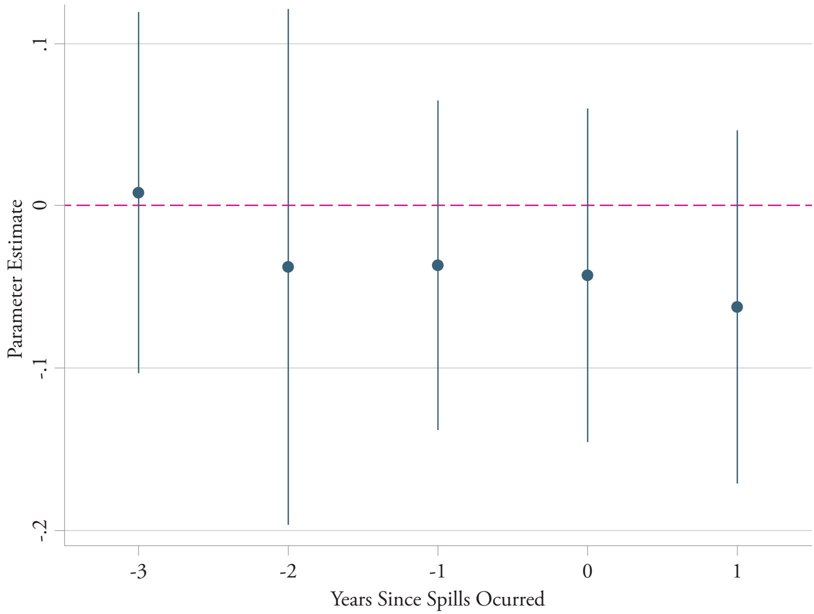
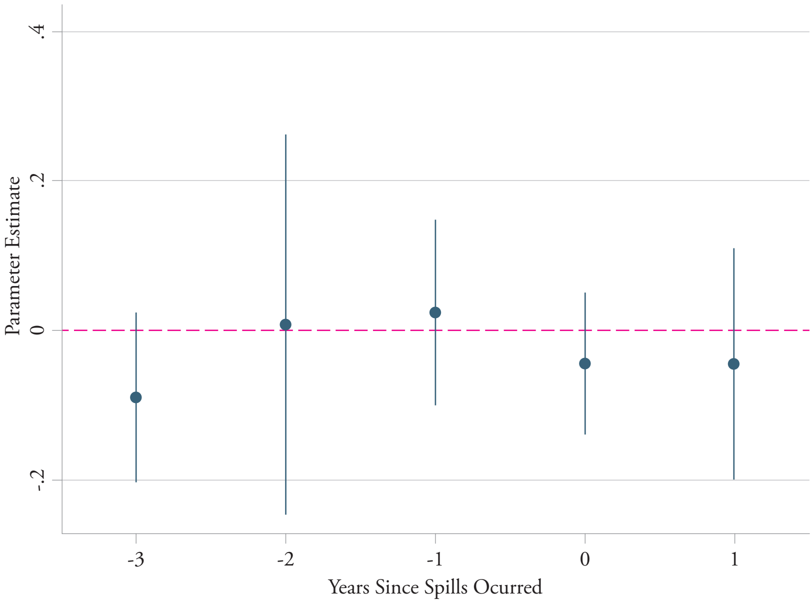
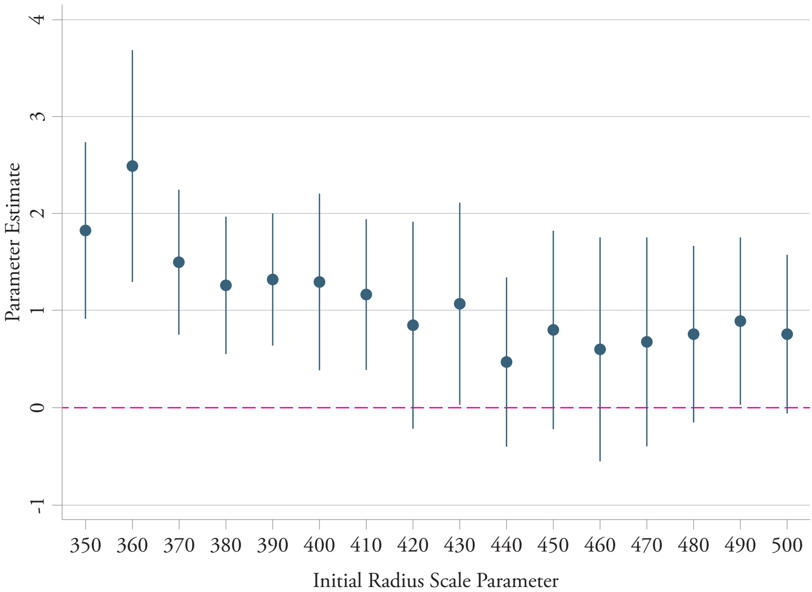


Figure A.1.6.
Event Study on Invisible Underemployment Rate



A.2. Overall Effect of Oil Spills[3]

Figure A.2.1.
Effect of Oil Spills on Real Monthly Salary



[3] Graphs show parameter estimates from regressions that controls for year and spill fixed effects, as well as time-varying covariates at individual and spill level. Regressions include an initial radius scale parameter ranging from 350 to 500. Whiskers indicate 95% confidence interval. Standard errors are clustered by district.

Figure A.2.2.
Effect of Oil Spills on Employment Rate in
Farming Activities

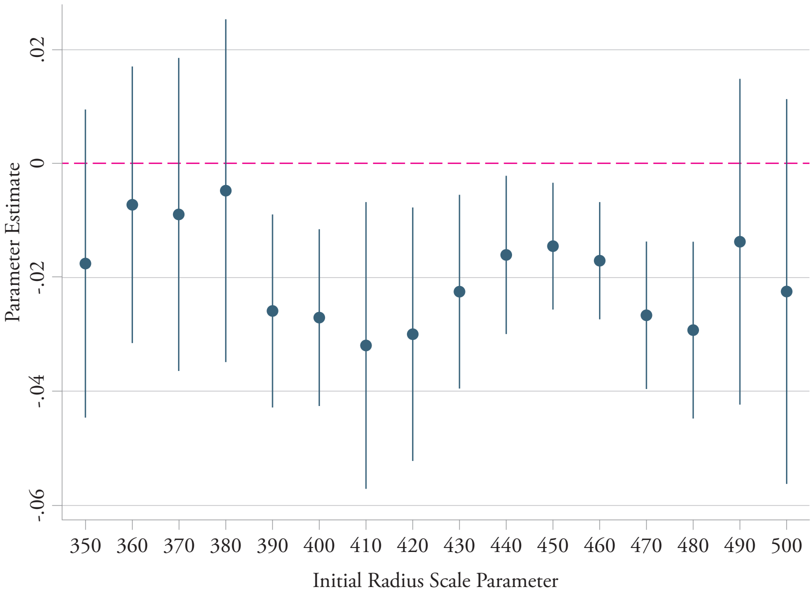


Figure A.2.3.
Effect of Oil Spills in Unemployment Rate

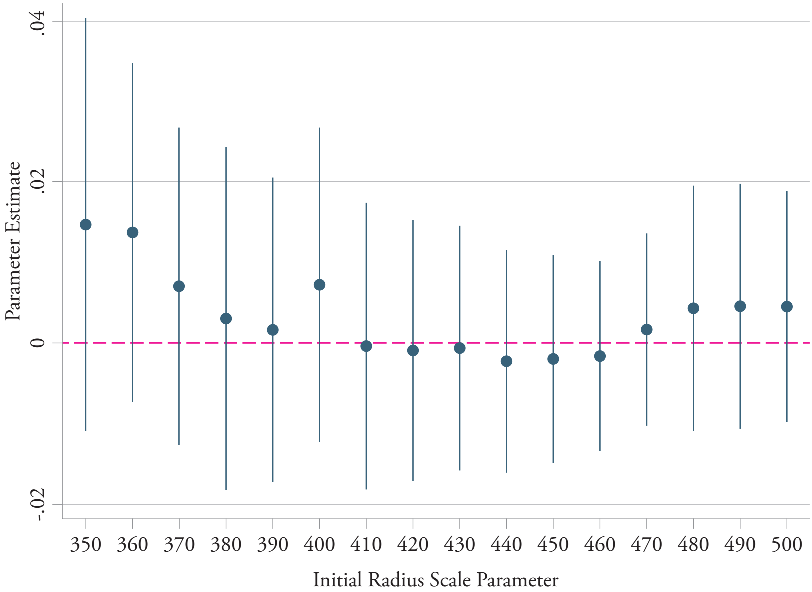


Figure A.2.4.
Effect of Oil Spills on Adequate Employment Rate

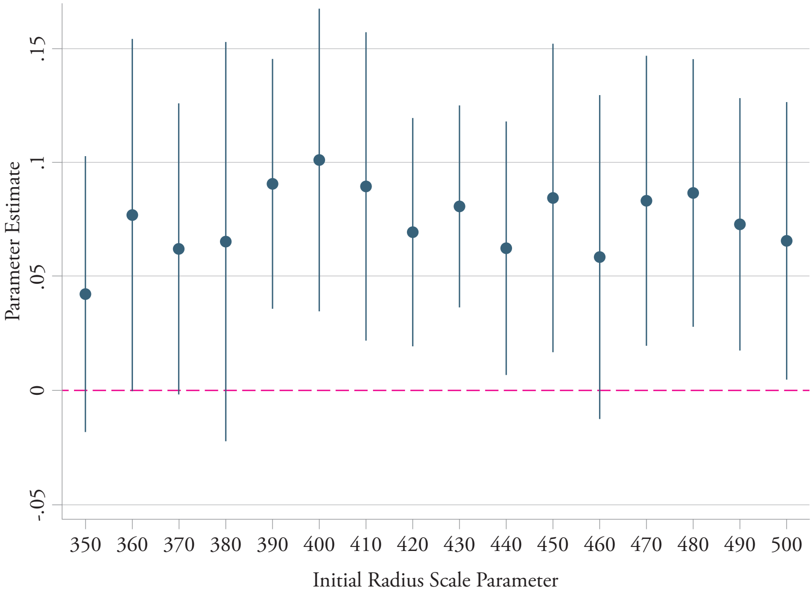


Figure A.2.5.
Effect of Oil Spills on Visible
Underemployment Rate

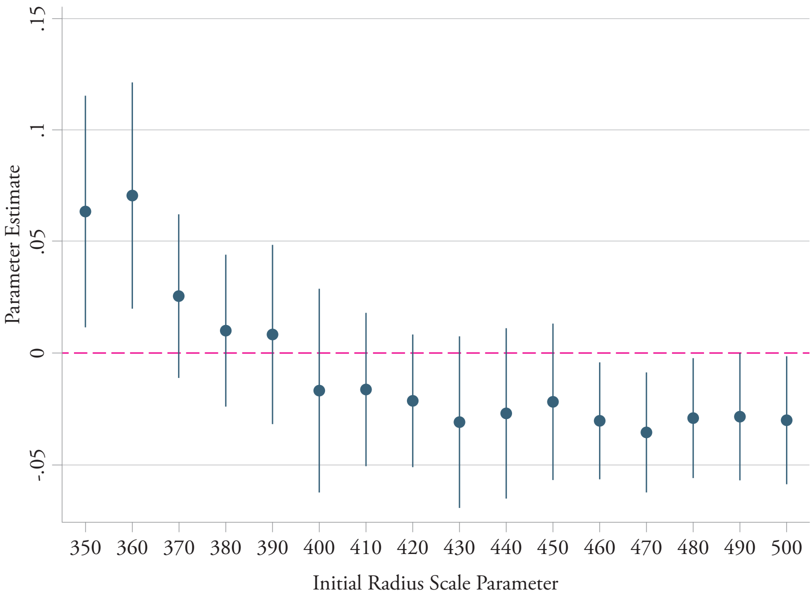
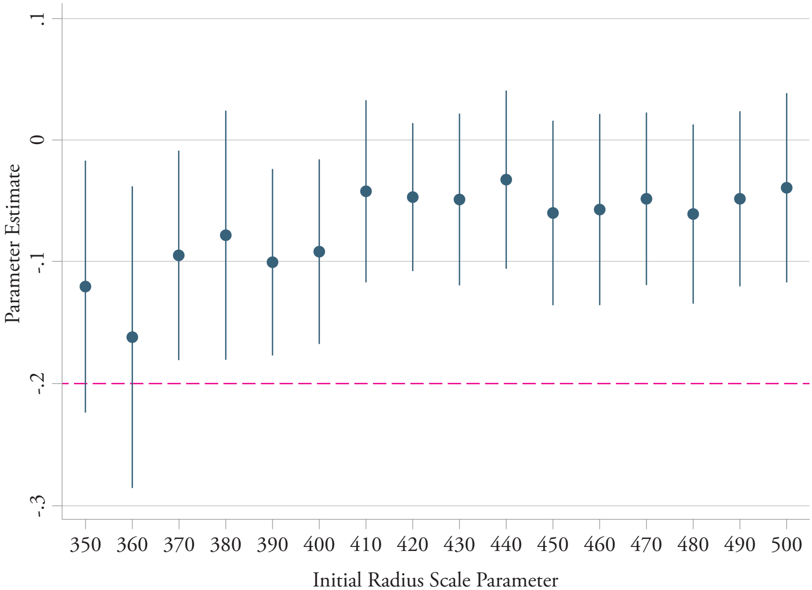
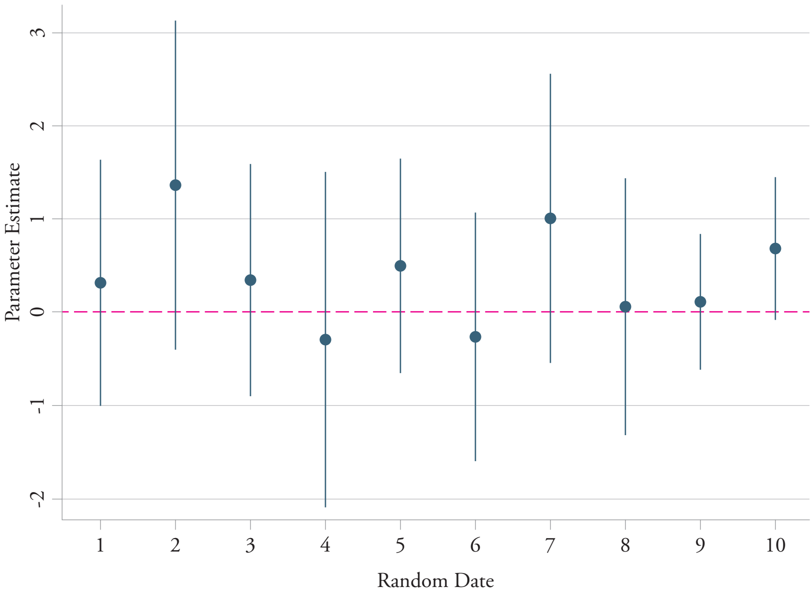


Figure A.2.6.
Effect of Oil Spills on Invisible
Underemployment Rate



A.3. Placebo Tests[4]

Figure A.3.1.
Placebo Test on Real Monthly Salary



[4] Graphs show parameter estimates for ten randomly selected dates of the year before the spills' occurrence, obtained from a uniform distribution. Regressions control for year and spill fixed effects, as well as time-varying covariates at individual and spill level. Regressions include an initial radius scale parameter of 400. Whiskers indicate 95% confidence interval. Standard errors are clustered by district.

Figure A.3.2.
Placebo Test on Employment Rate in
Farming Activities

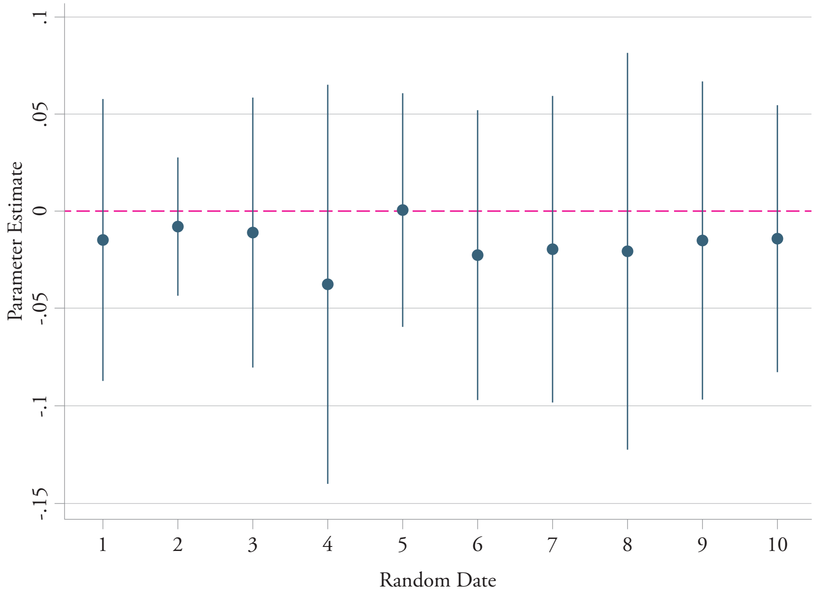


Figure A.3.3.
Placebo Test on Unemployment Rate

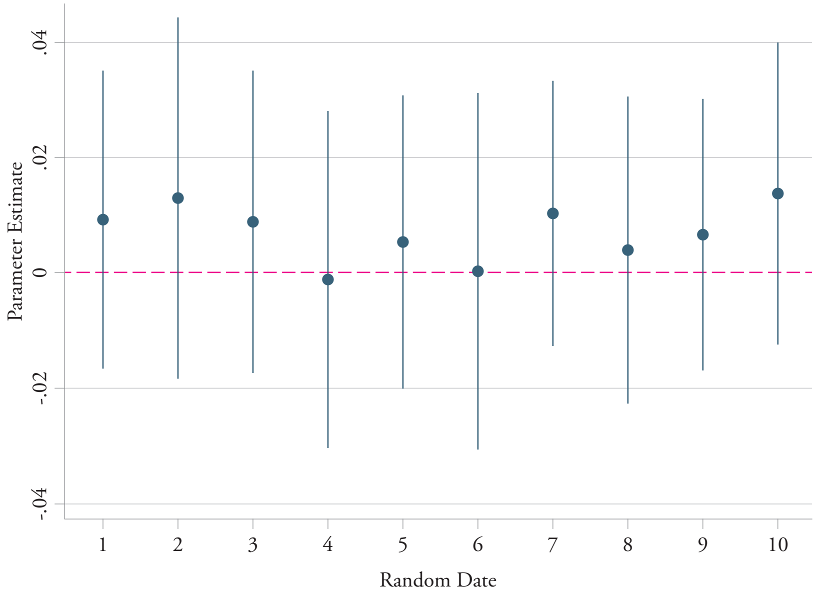


Figure A.3.4.
Placebo Test on Adequate Employment Rate

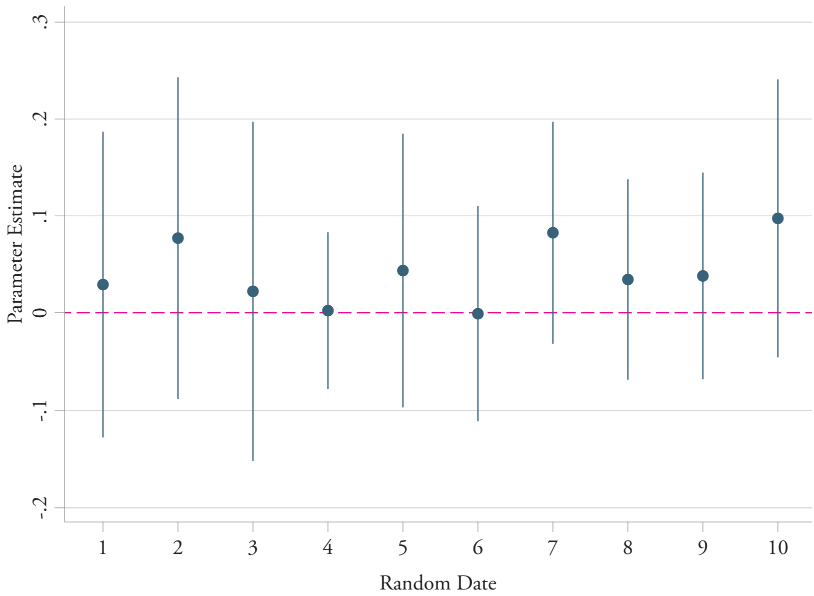


Figure A.3.5.
Placebo Test on Visible
Underemployment Rate

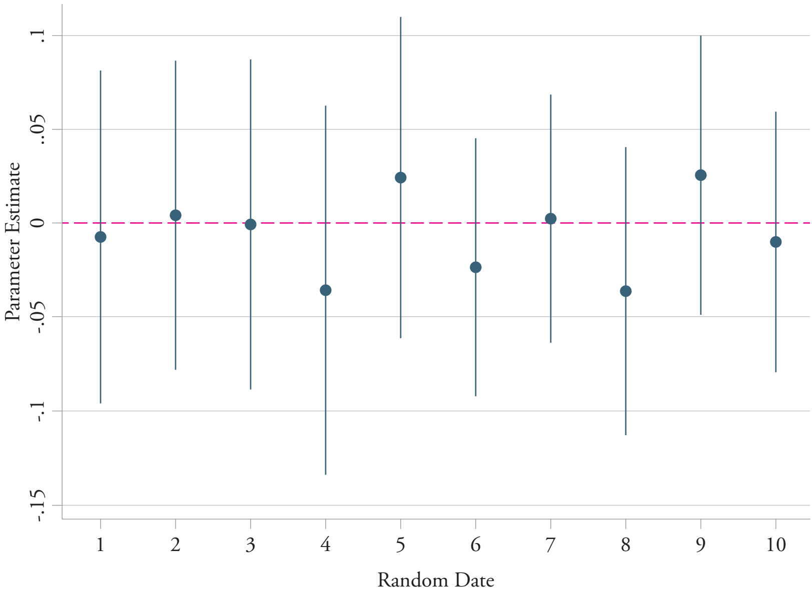


Figure A.3.6.
Placebo Test on Invisible
Underemployment Rate