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ABSTRACT

We Don’t Need No Education: The Effect of Natural Resource Income Shocks on Human Capital

We explore the effects of persistent income shocks on human capital using oil price fluctuations in a large sample of relevant African countries and employing micro data from multiple waves of the Demographic and Health Survey (DHS). Theoretically, such shocks enable human capital investment via the standard income effect; but also crowd it out because of substitutability between natural resource and human capital income sources - so the net outcome can go either way. Our model also suggests that the relative strength of the two effects depends on the age at which the shock is experienced and the affected gender. Consistent with these insights, we find that income shocks in early life enhance educational attainment and other derived outcomes; but reduce them if experienced in adolescence, especially for females. These results survive multiple robustness checks, and their broader implications are discussed.

JEL Classification: O12, I2

Keywords: human capital, income shocks, natural resources

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1 Introduction

Whether or not natural resources is a blessing or a curse has been a long standing subject of debate among economists. Indeed, a large literature has explored existence or the lack thereof of a resource curse: a possibly negative effect of natural resources on measures of economic performance, such as economic growth. This work has generated valuable insights on channels and mechanisms of influence, but overall ambiguous conclusions.[1] In particular, a subset of this literature has examined the effect of natural resources on schooling, both on its own and as a possible channel for the ultimate effect of resource abundance on economic growth. An early important paper Gylfason, 2001, argued for a negative effect, whereby natural resources crowd out human capital investment, and Papyrakis and Gerlagh, 2004, reinforce this conclusion. Some subsequent work, however, Sijns, 2006, Brueckner and Gradstein, 2016, provided contrarian evidence, arguing that income shocks resulting from natural resources are conducive to human capital investment. Even more recently, Abramson and Esposito, 2020, find that traditionally coal rich regions in Europe underinvested in universities in the long term – thus providing further evidence for crowding out of human capital by the abundance of natural resources. Geographically and temporarily closer to the scope of this paper, Ahlerup et al., 2020, detect similar detrimental effect in modern Africa in the context of gold mining. It appears, therefore, that evidence pertaining to the effect of natural resource wealth on human capital is contradictory.

In this paper, we take a more nuanced approach to the issue in order to possibly reconcile the different pieces of existing evidence. Conceptually, we argue that wealth generated through natural resources enables, via the standard income effect, a larger amount of human capital investment in the immediate run. On the other hand, the plausible lack of complementarity between this wealth and human capital implies potential crowding out in the future, so that the overall effect is ambiguous and depends, in particular, on the relative strength of these two elements. The return on human capital investment is a decisive factor in our conceptual framework in determining which of these two dominates. In particular, the higher the return the larger (and positive) the effect of natural resource income on education. A crucial element in the analysis then is the age range in which the child experiences such an income shock. If this happens in early childhood, the income effect dominates because the return on human capital investment is high; but this can be reversed if the shock occurs subsequently, in late childhood/adolescence. This theory plays a role in potentially explaining the wide range of results in existing (especially aggregate cross country) work, which typically ignores the specifics of school age distribution, such as Gylfason, 2001, and Papyrakis and Gerlagh, 2004, on one hand, and Sijns, 2006, and Brueckner and Gradstein, 2016, on the other hand.

To explore empirically the potentially differential impact of resource income

[1] A very partial sample of this literature includes Alexeev and Conrad, 2009, Aragon and Rud, 2013, Auty, 1994, Arezki et al., 2014, Black et al., 2005, Caselli and Michaels, 2013, Cavalcanti et al., 2019, Gradstein and Klemp, 2020, Papyrakis and Gerlagh, 2007, Sachs and Warner, 2001; Badeeb et al., 2017, and van der Ploeg, 2011, are useful surveys, and Havranek et al., 2016, conduct meta-analysis of hundreds of studies on the issue.

shocks on education depending on the child's age, we utilize the IPUMS-DHS dataset of oil producing African countries, whereby our primary focus is on income shocks generated through world oil price fluctuations. The dataset allows us to link oil price shocks at different ages in childhood to subsequent educational attainment. Although the sample countries are oil producers and net exporters, their share in the world oil output is typically small, so that oil price changes can be safely assumed as exogenous from their vantage point, hence can be interpreted as income shocks. By their nature, these shocks are persistent and can be interpreted as carrying a permanent income effect. Our empirical design differentiates between oil rich and oil poor regions in the sample countries and links outcomes to the differential incidence of oil price shocks by childhood/adolescence age brackets.

Our baseline results, supplemented by a variety of robustness checks, indicate that such shocks have a positive effect on education if experienced in early childhood (ages 0-4), but these shocks are statistically insignificant or are even detrimental for schooling when experienced later on (ages 10-14). These results are both consistent with the large and growing literature on future effects of early life circumstances, reviewed below, and with the work on resource curse, and it has the potential of reconciling the differing findings in these branches of research. We then also explore the role of gender in generating the above results and find that the early childhood positive effect is somewhat larger for boys than for girls, whereas the late childhood negative effect of oil price shocks on education is driven by the far larger effect for girls than for boys. Whereas the positive effect of early childhood shocks on education is well consistent with the established literature, the negative effect in later childhood, especially for girls, is a novel and important finding. It is consistent with the conceptual model, which indicates that, to the extent that returns from schooling and natural resource wealth are substitutes, income shocks in late childhood may result in less schooling. Additionally, we explore derived outcomes, such as households' wealth, women age of first marriage, and the number of children and find that their reaction to income shocks is broadly consistent with our conceptual framework and/or existing literature.

2 Literature and plan

A large volume of recent work documents the importance of early life circumstances for future outcomes and, specifically, for human capital; Almond and Currie, 2011, Almond et al., 2018, are excellent surveys. Adhvaryu et al., 2019, Fenske and Zurimendi, 2017, and Maccini and Yang, 2009, are examples of papers that exploit, as we do, income shocks for identification purposes. Our findings concur with this literature in detecting a positive effect of such shocks in early childhood; Lavy et al., 2016, specifically focus on educational attainment in this regard, whereas the above papers typically have education as one of their studied outcomes.

As our particular income shocks are derived from natural resource prices, our findings in this regard are consistent with Sijns, 2006, and Brueckner and Gradstein, 2016, and differ from Abramson and Esposito, 2020, and Papyrakis and Gerlagh, 2004. One possible difference between this research and those papers is the underlying social and economic environment. We are specifically interested in poor developing countries, whereas the above work also covers developed areas. Additionally, the above work, ignoring the underlying age structure of the population, potentially masks age related incidence of the shocks, which, we argue, is an essential factor generating important heterogeneous effects.

Our findings complement those in Ahlerup et al., 2020, whose focus, like ours, is Africa and, as who as we do, exploit changes in mineral (gold) prices for identification. Similar to our findings, these authors find that gold booms during adolescence induce less schooling; they attribute this to opportunities in the mining sector that increase the opportunity cost of schooling. This is inconsistent with our findings being driven by adolescent girls, who are less likely to benefit from work opportunities in the mining sector, see Kotsadam and Tolonen, 2016, for evidence in this regard. Additionally, Ahlerup et al., 2020, abstract form the more general analysis of the age incidence of income shocks.

In this latter regard, this research is more closely related to Shah and Steinberg, 2017, which detects a differential age effect of productivity shocks on educational attainment. Conceptually, however, productivity shocks, which both income and encapsulate substitution effects, are different from pure income shocks; and that paper's instrument for productivity shocks, annual rainfall, is very different from the instrument employed here, resource price shocks. Among other things, one crucial difference is that rainfall is a temporary shock, whereas resource price changes induce a persistent income shock. As will be elaborated more fully through our conceptual framework, this is important for the theoretical argument we make and serves as a primary channel through which age differential effect we empirically identify is induced. Further, child labor – common in the agricultural sector affected by rainfall – is much less prevalent in the oil industry, see Unicef, 2015.[2] We, therefore, do not expect productivity effects to play a major role in our setup.[3] Our contribution, therefore, can be viewed as complementary to Shah and Steinberg, 2017, and different from it both in conceptual and in contextual dimensions.

Finally, our gender related findings are well consistent with and reinforce, using our identification methods existing work, such as Alderman and King, 1998, Kingston, 2005, and Kaul, 2018. These papers typically document existence of a gender bias in educational investments and attainment in developing countries. While this is not the main focus of this paper, we contribute to the issue by documenting gender differences in educational attainment responses to early life shocks.

The rest of the paper proceeds as follows. The next section lays out our conceptual framework. Section 4 describes the data and empirical strategy. The main results are contained in Section 5, followed in Section 6 by robustness and extension analyses. Finally, Section 7 concludes.

[2]Vast majority of chlid labor in Africa (85 percent) takes place in agriculture and within family units; just less than 4 percent in industry, a fraction of which is in mining such as gold, diamond, copper and cobalt (ILO, 2017).

[3]This is one reason why the focus on oil price shocks – as opposed to price shocks of other minerals, such as gold or diamonds, where child labor is common – is advantageous for our purposes.

3 Conceptual framework

3.1 Baseline model

Consider a household consisting of a parent and a child living for two generation-periods. The first period income is equivalent to a windfall of I>0 and is allocated between family consumption, c_1, and schooling, s, subject to the budget constraint:

$$c_1 + s = I \tag{1}$$

Consistent with the empirical part, we interpret the income windfall as resulting from a natural resource. Stipulating existence of an additional income source in the first period would not change qualitative conclusions.

Schooling generates human capital, $h = H(s), H^{'} > 0, H^{"} < 0$. The return on human capital investment, equivalent to the future wage rate, is R_i. Index i corresponds to the child's age within the first generation-period, and we assume that the higher i the lower R_i, the rationale being that the younger the child when human capital investment is made, the larger the return – because learning begets learning, for example, see Almond and Currie, 2011, and Cunha and Heckman, 2007. [4]

Second period income is imputed to the child in her adult generation-period and consists of two parts. One is related to the windfall and equals I – which corresponds to a persistent oil price shock.[5] Another part is the wage, return earned on human capital, $R_iH(s)$. In principle, one could consider the two second-period income sources as either complements or substitutes; given that the source of income windfall in our empirical analysis is natural resource, it is common to assume that they are substitutes (as, for example, findings and discussion in Gylfason, 2001, strongly suggest).[6] We then write the second period income as $I + R_iH(s)$. Since the second period is the last one, all income is consumed, so we have:

$$c_{2i} = I + R_iH(s) \tag{2}$$

The parent derives utility from family consumption in period 1 and child's consumption in period 2:

$$U(c_1, c_{2i}) = c_1^{\epsilon} + \delta c_{2i}^{\epsilon}, 0 < \epsilon_1 < 1, \tag{3}$$

where $\delta > 0$ designates time preference – or is related to the extent of parental altruism.

[4]In principle, this mechanism could be incorporated into our model by dividing the first period into two learning sub-periods, in the manner it is done in Cunha and Heckman, 2007.

[5]Introducing a persistence parameter – so that the second period income would be, say, $\gamma I, \gamma > 0$ - would not change qualitative conclusions, although the intensity of persistence would play a quantitative role.

[6]A modicum of complementarity – such as skilled geologists and engineers needed to discovery and exploitation of oil fields or mines – would not change the analysis.

3.2 Analysis

Utility maximization with respect to schooling subject to the constraints (1) and (2) yields the following first order condition at the internal equilibrium:

$$FOC = -(I-s)^{\epsilon-1} + \delta R_i(I+R_iH(s))^{\epsilon-1}H' = 0 \tag{4}$$

And the second order condition,

$$\begin{aligned} SOC = & -(1-\epsilon)[(I-s)^{\epsilon-2} + \delta R_i^2(I+R_iH)^{\epsilon-2}H'] \\ & +[\delta R_i(I+R_iH(s))^{\epsilon-1}H''] < 0 \end{aligned} \tag{5}$$

holds. The derivative of the left hand side in (4) with respect to I is:

$$(1-\epsilon)[(I-s)^{\epsilon-2} - \delta R_i(I+R_iH)^{\epsilon-2}H'] \tag{6}$$

Evaluating this expression at the point where (4) holds, we obtain:

$$\begin{aligned} & (1-\epsilon)(I+R_iH)^{\epsilon-2}[(\delta R_iH')^{(\epsilon-2)/(\epsilon-1)}) - \delta R_i] \\ = & (1-\epsilon)(I+R_iH)^{\epsilon-2}\delta R_i[(\delta R_i)^{1/1-\epsilon}H'^{(\epsilon-2/\epsilon-1)} - 1] \end{aligned} \tag{7}$$

which is positive if and only if the bracketed expression is. Recalling the second order condition, upon totally differentiating (4), this directly leads to the following statement:

$$\begin{aligned} Sign(ds/(dI)) = Sign(-(\delta FOC/\delta I)/(SOC)) = Sign[(\delta R_i)^{1/1-\epsilon} \\ H'^{(\epsilon-2/\epsilon\text{-}1)} - 1] \end{aligned} \tag{8}$$

so that the effect of income windfall on schooling is positive whenever δR_i or when the return on human capital is sufficiently high. Recalling our interpretation that this return is an inverse function of a child's age in generation-period 1, we then have that the younger the child's age when experienced a shock, the higher the positive effect of income windfall on schooling.

Note that, in principle, even when $ds/dI < 0$, the second period aggregate income, hence consumption, can nevertheless be an increasing function of the income shock, as $dc_{2i}/dI = 1 + R_iH'ds/dI$, so that the possibly negative effect of income shock on schooling is likely to be offset by the pure income effect of the shock.

3.3 Introducing gender

Suppose now that the children differ by gender and let j, $j = m, f$, be the gender index. Each household's child is either a boy (m) or a girl (f). Then the budget constraint is:

$$c_1 + s_{ij} = 1 \tag{9}$$

The return on human capital investment, equivalent to the future wage rate, is R_{ij}, with $R_{im} > R_{if}$, so that the return to a male's HC is higher than to a female's HC – because of various gender barriers and social norms. The second-period consumption levels of the children are:

$$c_{2ij} = I + R_{ij}H(s_{ij}) \tag{10}$$

The parent derives utility from family consumption in period 1 and the child's consumption in period 2:

$$U(c_1, c_{2ij}) = c_1^{\epsilon} + \delta_j c_{2ij}^{\epsilon}, \tag{11}$$

It is common in the literature to assume that parents value boys more than girls for a variety of reasons, which would imply that $\delta_m > \delta_f$.

The above analysis then implies that the effect of income windfall on schooling is positive whenever $\delta_j R_i j$ is sufficiently high; particularly, if $(\delta_m R_{im})^{\frac{1}{(1-\epsilon)}} H'(s_{im})^{\frac{(\epsilon-2)}{(\epsilon-1)}} > 1 > (\delta_f R_{if})^{\frac{1}{(1-\epsilon)}} H'(s_{if})^{\frac{(\epsilon-2)}{(\epsilon-1)}}$- then this effect is positive only for boys.

A few concluding observations are in order. We first note that the above analysis abstracts from the potentially significant role of government policies. For example, governments typically tax natural resource wealth and use resulting revenues to, among other things, provide public schooling or subsidize privately provided education. While these are important factors, under plausible assumptions, they would not change our qualitative conclusions.

Additionally, the displayed income shock may stem from natural resource exploitation, as in the empirical analysis below - or from other sources; the only essential elements are that it be unconditional (on, say, school attendance) and permanent. In particular, many poverty alleviation income support programs have these features, and so share similarities with income windfall derived from natural resources. [7]

The gist of our argument, that elements of consumption smoothing take place under oil price generated shocks is supported by Hsieh, 2003. In fact, that paper's main objective is precisely to document this fact, in support of the permanent income hypothesis. Although the setup is different (Hsieh, 2003, considers income windfalls to Alaska's residents resulting from Alaska's Permanent Fund), the evidence strongly suggests that households take into full consideration future payments resulting from oil revenues when making current decisions.

Finally, the above analysis, indicating that the effect of natural resource wealth on human capital depends on the age at which its incidence took place has important aggregate implication. In the aggregate, this effect would depend on the age distribution, among other things, which may help explain the different conclusions obtained in existing scholarly work cited in the first two sections of the paper, which ignores this aspect. And the difference in results obtained in specific cases could potentially also be accounted for by such demographic factors.

[7] Albeit, there are also differences in details not modelled here, such as pollution possibly generated by the exploitation of natural resources. We believe, however, that these aspects are of a secondary importance to the issue at hand.

4 Data

4.1 Sample

Our data on education, wealth, and individual characteristics come from the individual census records conducted by Demographic and Health Survey (DHS) program. The data is retrieved from Integrated Public Use Microdata Series (IPUMS) International that reports harmonized representative samples. Our analysis is restricted to country survey waves with Global Positioning System (GPS) information on the location of the surveyed households. This is because the geocoded data allows us to assign individuals to their respective oil and non-oil producing regions allocated as explained below. To homogenize the sample, we focus on countries reporting at least one oil-producing region. This leaves us with 65 surveys over the period 1990-2016 for 16 countries: Angola, Cameroon, Democratic Republic of Congo, Ivory Coast, Benin, Ethiopia, Ghana, Madagascar, Namibia, Mozambique, Nigeria, Niger, Senegal, Tanzania, Egypt, and Morocco.

The sampled countries had a population of 757 million people in 2016 representing 62 percent of Africa's population. In assigning oil locations and consequently households, we choose to work on coarser administrative units (ADM 1, or provinces) rather than finer levels (ADM 2, or district). The advantage of this approach is twofold. First, higher administrative levels allow for reducing the measurement error associated with the allocation of oil fields. Second, focusing on provinces can mitigate migration concerns, which is a common phenomenon in periods of high oil prices. Even though migrating from one province to another is possible, it is less frequent as compared migrating from one district to another, especially in the presence delimited ethnic and tribal territories making movement quite restricted. Our sample includes 247 provinces with a mean (median) size of 49 (29) thousands km squared. Figure 1 shows a map of the countries included along with the locations of oil provinces.

4.2 Outcomes

Education.—Our main outcome variable is individual's educational attainment measured by the number of years of education. To obtain this information, we make use of two types of surveys: Women surveys covering women aged 15-53 years old; and Men surveys including male respondents aged 15-56 years old. Our total sample consists of 580,478 individuals born between 1960 and 2001, with 137,924 observations belonging to male respondents, and 442,554 observations representing female respondents. Note that country coverage differs between the two surveys, particularly for male surveys with Egypt and Morocco not included.

Wealth.—To measure household's wealth, we construct a wealth index (WI) using information on household characteristics such as household's possession of consumer durable goods, access to basic services, and housing condition. These indicators are then entered into a factor analysis -using the Principal Component Analysis- from which the first factor is selected to derive the asset weights and consequently the wealth index. The obtained WI is rescaled, so that it ranges from 0 to 100, with

0 representing households having no assets and living in lowest quality housing, and 100 representing households possessing all assets and living in highest quality housing. The advantage of using our WI over the wealth index provided by the DHS lies in the fact that latter is only calculated at the country level, making it only possible to compare households relative to othe households within a given country. In contrast, the WI can be easily used to compare the households' wealth level across provinces, since it uses the same combination of assets and standard assets' weights to rank households independently of where they live.

Additional outcomes.—We also consider additional outcomes, such as women age at first marriage, the number of children, employment and type of occupation, work frequency, and husband's level of education and employment the source of which is the women DHS questionnaires.

4.3 Independent variables

The main independent variables are an indicator for oil provinces, international oil prices and their interaction.

Oil provinces are allocated based on the map of world oil deposits from PRIO petroleum dataset (Lujala et al., 2007). Onshore oil deposits were assigned to a given province, if the centroid of the deposit lie within its boundaries. For offshore oil deposits, we first calculated the distance between the centroids of the province and the deposit and assigned the latter to the nearest province. International oil prices are given by the average of Dubai, Brent and Texas prices expressed in real 2010 USD and taken from the World Bank Commodities prices dataset.

Other variables.—The DHS contain a set of demographic information for both men and women, which we use to construct birth cohorts and control for individual characteristics. These include age, religion, place of residence (i.e. urban vs. rural) and sex of the household head.

4.4 Descriptive statistics

Our sample consists of more than 580,000 individuals interviewed over period from 1990 to 2016. Table 1 report some descriptive statistics of our main variables of interest. Several features are worth mentioning. First, individuals residing in oil regions have on average more years of schooling than their peers in non-oil regions, and the difference is statistically significance. Male (female) respondents in oil regions possess on average 2.5 (2.6) more years of schooling. Second, within both oil and non-oil regions, male respondents have more years of schooling than female respondents, and the difference is larger in non-oil regions. Third, the highest attained educational level for an individual is, on-average, 7.3 years in oil regions, which is equivalent to the completion of primary education plus some post primary education. In non-oil regions, on average individuals do not manage to complete primary education. Similarly, the household wealth tends to be higher in oil regions than in non-oil regions, with more wealth possessions reported by male respondents than female respondents.

5 Empirical Strategy

Our conceptual framework proposes two main testable hypotheses: (1) a positive income shock has differential effects on the educational attainment - and wealth - depending on the age of the child, with positive effects dominating at early life of a child; (2) the positive effects are larger for male children compared to female children. To test these hypotheses, our empirical strategy looks at the effect of oil price shocks at different periods of individual's life and across gender. Our baseline specification takes the following form:

$$Y_{irBt} = \beta(OPS_{Bt} \times OilProvince_r) + \alpha X_{iBt} + \phi_{Bt} + \delta_r + \delta_r \times Bt + \epsilon_{irBt} \qquad (12)$$

where the outcome Y_{irBt} is either the years of schooling or, alternatively, the aggregate household's wealth of individual i born in year B and residing in province r during the age interval $t(1, 2, 3)$. We focus on three periods over the individual's life course: (i) pre-school years ($t = 1$, ages 0-4); (ii) primary school years ($t = 2$, 5-9); and (iii) years with completed primary education and some post-primary education ($t = 3$, 10-14), referred sometimes to as adolescence. OPS_{Bt} is the logarithm of the five year moving average of real oil prices. $OilProvince_r$ is a dummy variable that takes a value of 1, if a given province is producing oil. ϕ_{Bt} is age interval fixed effects to capture period-varying shocks that are common across individuals in a cohort, and δ_r is provincial fixed effects to control for time-invariant unobserved heterogeneity at the province level. The $\delta_r \times Bt$ is provincial-specific time trend to account for provincial trends that might be correlated with both educational attainment and oil prices. X_{iBt} is a set of time-varying controls at the individual level including indicators for urban residency, religion, female household head, month of survey, and year of survey.[8] The above equation is estimated on the full sample of individuals and separately for both men and women to reflect potential gender heterogeneous effects. When estimating the full sample, we also for control for gender. Standard errors are clustered at the province level.

Our approach assumes that oil prices are exogenous, which is plausible because, with the exception of Nigeria and Angola, most of our sampled countries are low oil-producing countries contributing less than 1% to total world oil production. For Nigeria and Angola, despite being the largest two oil-producing countries in Africa, their production in 2016 accounted for only 2% of world production each.[9] Furthermore, by interacting oil prices with indicators for oil provinces conditional upon provincial and age-interval fixed effects, we are exploiting differential effects of oil price changes depending on access on oil in the spirit of a difference-in-difference strategy, whereby individuals from the same birth cohort are divided into treatment and control groups, depending on the experience of an oil price shock.

Based on our hypotheses, we expect the sign of β to be positive at period $t = 1$, or during early childhood years with effect being relatively larger for male children compared to their female peers. For the next two periods, the sign of β could be

[8] As annual oil prices are colinear with year fixed effect, the presence of variables capturing the latter component implies that the average effect of the former is accounted for.

[9] https://www.cia.gov/library/publications/the-world-factbook/rankorder/2241rank.html

either positive or negative, with the former being smaller in magnitude compared to period 1. If β is negative, then we would expect the negative effect to be larger for females.

6 Main results

6.1 Educational attainment

We begin by taking a broad look at the data. To this end, we run an OLS regression on our sample, with the outcome variable being years of schooling attained by resident i in region r; and the main explanatory variable being $(OPS_{0-14} \times OilProvince_r)$, where OPS_{0-14} is the logarithm of the 14 year moving average of real oil prices, and $OilProvince_r$ is a dummy variable that takes a value of 1, if a given province is producing oil. Table 2 presents the results. For the entire sample, in columns 1 and 2, they are insignificant when only region, region specific time trend, and age group fixed effects are included as control variables, and just barely significant (at 10% level) when all controls are included, in which case the negative estimated coefficient implies that oil price shocks experienced in childhood reduces the subsequent educational attainment. When the analysis is decomposed by gender, in columns 3-6, it turns out that the negative effect of oil price shocks on educational attainment is driven through the effect on females; the male regression returns insignificant results.

We then proceed with our main analysis, by age groups, as the above analysis potentially masks differences across those. The results of estimating equation 12 are presented in Table 3. They indicate (see Panel A) that oil price shocks experienced in early childhood enhance subsequent educational attainment, in the entire sample, and separately for females and males. This is consistent with the vast literature on the effect of early childhood income shocks on future outcomes, such as Fenske and Zurimendi, 2017, in the context of Nigeria's oil price shocks. Interestingly, and a new finding relative to the early childhood perspective, oil price shocks experienced between the ages 5-9 have an insignificant effect on subsequent educational attainment for neither gender group, nor for the entire sample, see Panel B.

Even more interesting is the negative effects of such shocks in early adolescence (ages 10-14) on subsequent educational attainment, Panel C. While these results are obtained for each of the gender groups (as well as for the full sample), it is more pronounced for women, with 1% of statistical significance. Not only are these results statistically significant, they are also economically meaningful. Thus, recalling our regression specification, the estimated coefficients, between -0.45 and -0.25, indicate that a one percent increase in the average oil price during the 10-14 age decreases subsequent educational attainment in oil producing regions by a third of the year. A back of the envelope calculation may help to translate these figures into elasticities. A one percent increase in the average oil price can be estimated to be about five percent aggregate increase over the adolescence period. And, since the average of years of schooling in our sample is 5.3, the decrease of a third of the year constitutes some seven percent of this average. With the five percent increase in the oil price results being equivalent to a seven percent decrease in schooling, it then follows that the elasticity of educational attainment of an adolescent individual with respect to an oil price shock is about -1.4 on average.

These results are consistent with our theoretical framework in two ways. First, they indicate that oil wealth increase experienced in adolescence may be detrimental for schooling; and, consistently with the model, they are particularly pronounced for women. Whereas the former is consistent with Ahlerup et al., 2020, who find that gold booms are detrimental for schooling of 12 year old, the latter result differs from that paper's suggestions in detecting a larger effect on female gender.

6.2 Wealth

Eventual wealth later in life is our secondary outcome of interest. Our conceptual framework indicates that income shocks have a positive effect on accumulated wealth because of the standard income effect, but either a positive or a negative effect via the schooling channel. This then implies that both effects operate in the same positive direction in early childhood, but their joint outcome can be ambiguous in adolescence, depending on the relative strength of the two effects.

In Table 4 we, therefore, replicate our analysis using wealth as the outcome variable. Panel A in that table confirms the positive effect of early childhood income shocks on subsequent wealth, and Panel B presents insignificant results for the 5-9 age group. Panel C yields negative coefficients for the entire sample as well as for each of the two gender groups, indicating that the results with respect to wealth are qualitatively similar to those with respect to schooling. In particular, positive oil shocks in adolescence reduce subsequent wealth. While this finding is also of an independent interest, our above analysis suggests that the reduction in educational attainment is a possible channel for this outcome.[10]

7 Robustness and extension

We now carry out several robustness checks. They pertain to various selections of the sample regions and periods; the population demographics; prices of other minerals than oil; and interrelationship between shocks experienced at different ages in childhood/adolescence.[11] We also consider variations on the construction of the wealth index, and explore additional outcomes as an extension.

7.1 Countries' and period selection

We first explore the robustness of our results to the sample of countries in the main analysis. To this end, we cut the sample in several ways. In Table 5, columns 1-3, we focus on two biggest oil producing countries in our sample, Nigeria and Angola. We

[10]There may also be additional channels directly related to natural resource curse, as briefly reviewed in the Introduction.

[11]These robustness results are presented for educational attainment as the outcome variable, but they also broadly hold for the wealth index as well.

observe that relative to the baseline results, while the results remain qualitatively unchanged, both their statistical and economic significance increase. Thus, in this context, oil price shocks in the lowest (highest) age group positively (negatively) affect future schooling attainment, typically at the 1% statistical significance level. We also replicate, in columns 4-6 of Table 5, our baseline analysis for a group of countries (Angola, Nigeria, Egypt, Congo and Morocco) that have continuously produced oil beginning in 1960 – the earliest year for which we have data from the DHS. Again, like in the case of Nigeria and Angola, the results are only reinforced relative to the baseline analysis.

We then alternatively drop countries with only one oil producing region (which leaves us with 177 regions as opposed to 247 in the full sample). Here, the results (presented in Appendix Table A1, columns 1-3) are not substantively different from those in the main analysis. Likewise, when non-oil producing African countries are added, the results (in Appendix Table A1, columns 4-6) remain qualitatively unchanged, although their statistical significance not surprisingly drops.

Oil prices spiked in the post 1973 period, and one may wonder if this structural break may have affected the identified effects. To this end, we replicate our analysis for the post 1973 period – which reduces our sample by more than 15 percent; yet, the results remain essentially the same, see Table 5, columns 7-9.

7.2 Demographics

In Table 6, we restrict our sample to respondents being at least 18 years old, the standard high school graduation age. This reduces the sample by almost fifteen percent, but leaves our baseline results almost unchanged qualitatively. We then consider the possibility that migration may have a bearing on our results. To this end, we define a non-migrant as a respondent who has always resided in her current place of residence and introduce an additional control variable – the interaction term between oil price shock and the non-migrant dummy. The results, in Appendix Table 2, are by and large very similar to the baseline results, and the newly introduced control is never significant.

7.3 Prices of other minerals

Africa's continent is rich with minerals, and one potential concern is that our results might be driven by fluctuations in the prices of those minerals as opposed to that of oil. To alleviate this concern, we introduce in our baseline regression as an additional control variable prices of other minerals interacted with their producing region. We specifically focus on gold, silver, aluminum, copper, lead, nickel, zinc and tin. This choice is dictated by the following two main consideration. For one, a mineral has to be of at least some importance for at least one country in our sample; and the country should not be a major world producer of the mineral so as to be able to affect its price. We then construct the variable, mineral price shock, as follows. For each region in our sample, we select the main mineral produced based on the frequency of the production of this mineral across different mines which is crosschecked by the main minerals that the country is producing.[12]This enables us to construct a dummy variable for each region indicating presence of lack thereof of a main mineral. Multiplying this variable by the mineral's price yields mineral price shock index, which is then constructed similar to the oil price shock. Regression results are shown in Table 7. Comparing with respective columns 2, 4, and 6 in Table 2, we observe that the main coefficients of interest in columns 1, 2, and 3, get marginally reduced (in absolute value), but still remain significant. In particular, one of our main findings, that oil price shocks are detrimental for schooling when experienced in adolescence, remains highly significant.

7.4 Controlling for early life shocks

While our results with respect to the positive effect of early life shocks on subsequent educational attainment and wealth are not too surprising in the light of much existing work on the subject, the negative effect of shocks in adolescence is more novel. To further tease out this result, we now would like to more clearly separate this type of shock from the early life shock.[13] To do so, we run a regression with adolescence shocks, now controlling for early life (ages 0-4) shocks. The results, in Appendix Table 3, while indicating a reduced significance for the males sample, continue to hold. In particularly noteworthy is the highly significant negative effect of the shock in the female sample.

7.5 Modifications of the wealth index

Our construction of the wealth index combines several household amenities and aggregates them via the principal component procedure. We now conduct some robustness exercises with respect to amenities' selection (using the same aggregation procedure throughout). In Appendix Table A4, we add the number of sleeping rooms in the house as yet another attribute; and in Appendix Table A5 we omit two items least correlated with the principal component, namely, radio and bike ownership. As can be seen, the results remain virtually unchanged relative to the baseline analysis in Table 4.

7.6 Other outcomes

Our main result indicates that early life (adolescence) income shocks positively (negatively) affect female educational attainment. We now consider additional outcomes pertaining to adult female circumstances, specifically, age at first marriage, the number of children, employment and type of occupation, work frequency, and husband's level of education and employment. The results, in Table 8, column 1, indicate that early life (adolescence) income shocks increase (reduce) females' age at first

[12]Minerals are allocated to regions using the Mineral Resources Data System (MRDS) from U.S. Geological Survey (USGS) (https://mrdata.usgs.gov/mrds/).

[13]Annual oil prices are autocorrelated, but this autocorrelation is much less pronounced over the span of a decade.

marriage, which is consistent with broad empirical regularities, specifically, the positive association between female schooling and age of marriage as documented in sociological literature, see Saardchom and Lemaire (2005). Further, as follows from Table 8, column 2, early life (adolescence) income shocks reduce (increase) their number of children. Recalling our main result, this finding indicates that early life income shocks enhance women schooling and also reduce their number of children as has been extensively documented in general (Cochrane, 1978); for poor countries (Schultz, 19898); and, specifically, in Africa's context (Osili and Long, 2008). In columns 3 and 4, we check whether early life (adolescence) income shocks affect women's employment status and type of occupation. Results show that these income shocks do not have a statistically significant impact on women's likelihood to be employed; however, the quality of the job matters. Early life (adolescence) income shocks increase (reduce) females' chances to get a skilled job, which is not surprising given that skilled jobs require a higher level of educational attainment. Finally, columns 6-8 show that females who have experienced income shocks in their childhood are more likely to work on all year basis and have a partner with active employment status; in contrast, females who have experienced that in their adolescence years are less likely to work on annual basis and more likely to have a partner who is not working. However, income shocks do not seem to affect the partner's educational level of attainment in a statistically significant manner.

8 Conclusion

Whether or not natural resource wealth is a blessing or a curse in general and with respect to human capital accumulation, specifically, has been a long-standing subject of interest for economists. Existing literature has come up with contradictory conclusions in this regard. We contribute to this literature studying how income shocks resulting from oil price fluctuations have affected educational attainment, ultimate household's wealth, and additional derived outcomes, depending on children age of incidence of these shocks and utilizing a large sample of Africa's households. The proposed conceptual framework used to organize thinking about the issue, indicates that incidence timing is crucial, whereby the potentially positive affect of income shocks on educational attainment (and future wealth) diminishes with a child's age, possibly turning to being negative if the income shock is experienced in adolescence, with a more pronounced decline among girls than boys. The mechanism at work is simply the crowding out of educational investment by a resource income windfall.

Our empirical analysis generates results consistent with the above theoretical hypotheses. In particular, and in line with the vast existing work, we document that income shocks in early childhood (ages 0-4) have a positive effect on subsequent educational attainment and wealth, for both gender groups. More surprisingly, however, we find that income shocks in adolescence (ages 10-14) have a negative effect on both outcomes, especially for girls. These results hold under a variety of robustness checks and they are economically significant. Focusing on adolescent girls who have experienced a positive oil price shock, we further find that they tend to marry earlier and have more children than those who have not experienced such a shock. These findings are consistent with those on educational attainment and with existing literature documenting that education causes women to marry later and to have fewer children.

Summarizing, therefore, this research depicts a convoluted picture of the effect of income windfalls resulting from natural resources on schooling and associated outcomes that crucially depends on the incidence period of such windfalls. Our results may help to reconcile the often contradictory findings pertaining to the effect of natural resource wealth on educational attainment and indicate that the aggregate effect depends on the age distribution of the affected children. Further, such income windfalls have important distributional consequences across the households, depending on the age and gender distribution of the children within a household. Without paying a careful attention to these aspects, the assessment of the effects of income shocks may yield biased results.

While the empirical analysis relies on income shocks stemming from oil price fluctuations, our theoretical model suggests that the basic mechanism at work can be applicable to any persistent (unconditional) income shock that has the potential to crowd out educational investment. This may have policy implications, indicating in particular that a permanent unconditional income transfer may under certain circumstances be an impediment for educational attainment, especially for women, and detrimental even for ultimate household's wealth and related outcomes. This is an important observation for future research as many existing poverty alleviation income support policies rely precisely on this type of income transfers. Hence, the results of this research may inform policy makers as to potential pitfalls of such programs.

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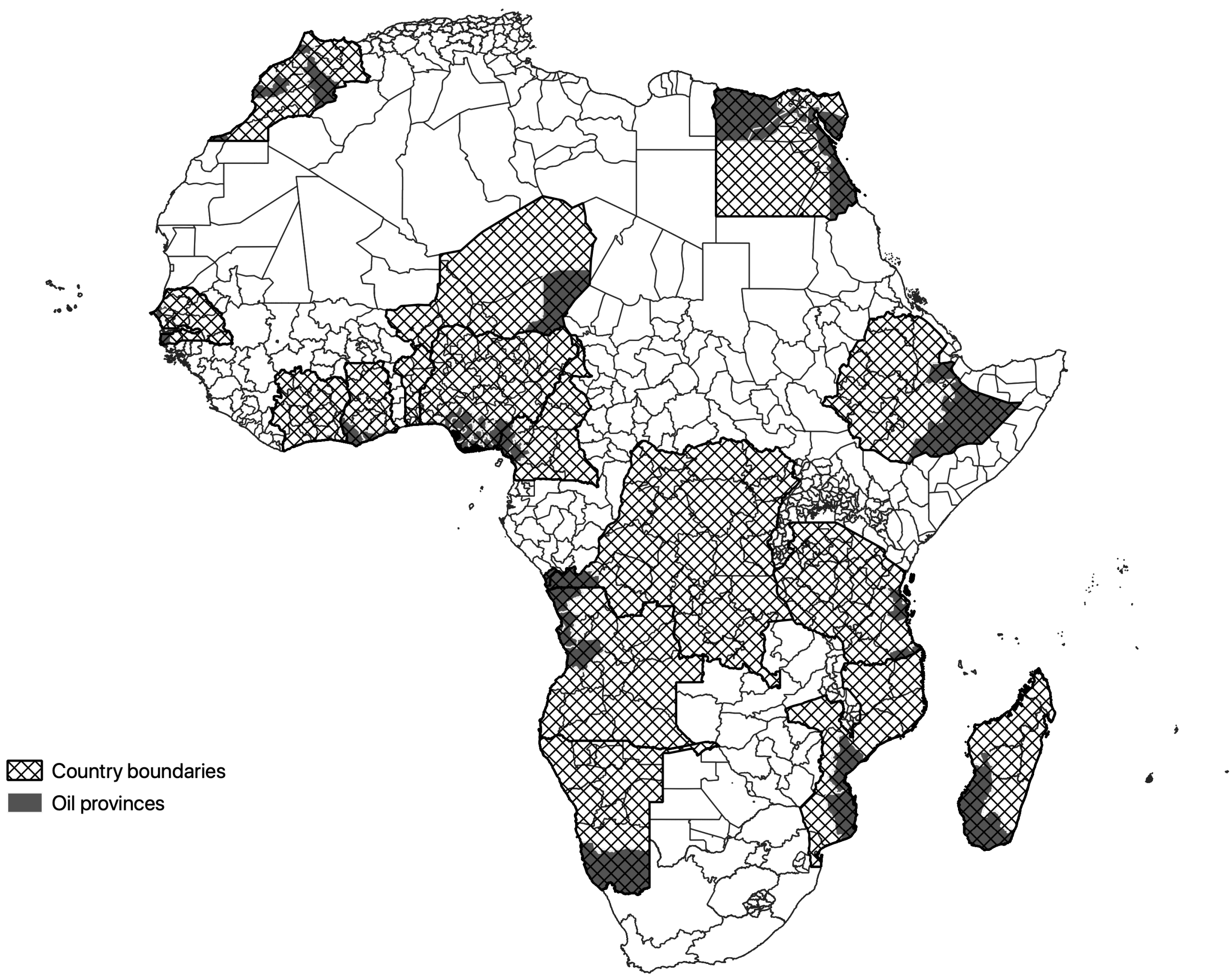

Figure 1: Location of oil provinces

Table 1: Summary statistics

Variable	N	Mean	SD	Min	Max	Difference
Education						
Oil regions (All sample)	112,982	7.330	4.836	0	24	***
Oil regions (Male sample)	27,854	8.430	4.455	0	24	***a
Oil regions (Female sample)	85,128	6.970	4.901	0	24	***
Non-oil regions (All sample)	467,496	4.802	4.832	0	24	
Non-oil regions (Male sample)	110,070	6.032	4.801	0	24	
Non-oil regions (Female sample)	357,426	4.423	4.778	0	24	
Wealth						
Oil regions (All sample)	112,982	0.861	2.431	-1.608	8.274	***
Oil regions (Male sample)	27,854	1.314	2.359	-1.608	8.274	***a
Oil regions (Female sample)	85,128	0.712	2.435	-1.608	8.274	***
Oil regions (All sample)	467,496	-0.165	1.986	-1.608	8.274	
Oil regions (Male sample)	110,070	0.024	2.003	-1.608	8.274	
Oil regions (Female sample)	357,426	-0.223	1.977	-1.608	8.274	
Log oil price						
Period 1	580,478	3.049	0.660	1.803	3.962	
Period 2	580,478	3.231	0.550	1.803	4.340	
Period 3	580,478	3.458	0.451	2.437	4.504	

[a] indicates the different between male and female samples is satistically significant at 1% significance level. Difference is based on nonparametric K-sample test on the equality of medians.

Table 2: The effect of OPS experienced in all age groups together

	(1)	(2)	(3)	(4)	(5)	(6)
	All Periods (0-14 years old)					
	Education	**Education**	**Education**	**Education**	**Education**	**Education**
	Full sample	**Full sample**	**Male sample**	**Male sample**	**Female sample**	**Female sample**
Oil price shock × Oil Province	-0.190	-0.210*	0.025	0.017	-0.246*	-0.268**
	(0.127)	(0.119)	(0.144)	(0.145)	(0.131)	(0.126)
Controls	No	Yes	No	Yes	No	Yes
Number of observations	580,478	580,478	137,924	137,924	442,554	442,554
Number of regions	247	247	220	220	247	247
R-squared	0.320	0.420	0.297	0.387	0.350	0.431
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the number of years of education. Oil price shock is the ln-14 years average of oil price for period t multiplied by a dummy that take a value of 1 if the region is producing oil. Controls include year of survey, month of survey, religion, urban residency, and sex of household head. For the full sample, we control for gender. The method of estimation is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the region level. Significantly different from zero at *10% significance, **5% significance level, ***1% significance level.

Table 3: Main education results: the effect of OPS experienced in different age periods

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Period 1 (0-4 years old)					
	Education	**Education**	**Education**	**Education**	**Education**	**Education**
	Full sample	**Full sample**	**Male sample**	**Male sample**	**Female sample**	**Female sample**
Oil price shock × Oil Province	0.238**	0.190*	0.227**	0.203**	0.219**	0.184*
	(0.105)	(0.097)	(0.097)	(0.099)	(0.106)	(0.101)
Controls	No	Yes	No	Yes	No	Yes
Number of observations	580,478	580,478	137,924	137,924	442,554	442,554
Number of regions	247	247	220	220	247	247
R-squared	0.320	0.420	0.297	0.387	0.350	0.431
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B. Period 2 (5-9 years old)					
Oil price shock × Oil Province	-0.062	-0.084	0.064	0.057	-0.097	-0.120
	(0.080)	(0.075)	(0.097)	(0.093)	(0.081)	(0.078)
Controls	No	Yes	No	Yes	No	Yes
Number of observations	580,478	580,478	137,924	137,924	442,554	442,554
Number of regions	247	247	220	220	247	247
R-squared	0.320	0.420	0.297	0.387	0.350	0.431
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes	Yes	Yes	Yes
	Panel C. Period 3 (10-14 years old)					
Oil price shock × Oil Province	-0.452***	-0.397***	-0.269**	-0.240*	-0.472***	-0.436***
	(0.121)	(0.124)	(0.127)	(0.139)	(0.125)	(0.126)
Controls	No	Yes	No	Yes	No	Yes
Number of observations	580,478	580,478	137,924	137,924	442,554	442,554
Number of regions	247	247	220	220	247	247
R-squared	0.320	0.420	0.297	0.387	0.350	0.431
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the number of years of education. Oil price shock is the ln-5 years average of oil price for period t multiplied by a dummy that take a value of 1 if the region is producing oil. Controls include year of survey, month of survey, religion, urban residency, and sex of household head. For the full sample, we control for gender. The method of estimation is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the region level. Significantly different from zero at *10% significance, **5% significance level, ***1% significance level.

Table 4: **The effect of OPS experienced in different age periods on future wealth**

	(1)	(2)	(3)
	Panel A. Period 1 (0-4 years old)		
	Wealth	**Wealth**	**Wealth**
	Full Sample	**Male sample**	**Female sample**
Oil price shock × Oil Province	0.647**	0.849**	0.592**
	(0.270)	(0.345)	(0.295)
Controls	Yes	Yes	Yes
Number of observations	466,754	129,652	337,102
Number of regions	247	220	247
R-squared	0.455	0.458	0.456
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes
	Panel B. Period 2 (5-9 years old)		
Oil price shock×Oil Province	0.042	0.208	-0.001
	(0.242)	(0.408)	(0.252)
Controls	Yes	Yes	Yes
Number of observations	466,754	129,652	337,102
Number of regions	247	220	247
R-squared	0.455	0.457	0.456
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes
	Panel C. Period 3 (10-14 years old)		
Oil price shock × Oil Province	-0.899***	-0.821*	-0.942***
	(0.314)	(0.426)	(0.328)
Controls	Yes	Yes	Yes
Number of observations	466,754	129,652	337,102
Number of regions	247	220	247
R-squared	0.455	0.457	0.456
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes

The dependent variable is the household wealth index constructed as explained in text. Oil price shock is the ln-5 years average of oil price for period t multiplied by a dummy that take a value of 1 if the region is producing oil. Controls include year of survey, month of survey, religion, urban residency, and sex of household head. For the full sample, we control for gender. The method of estimation is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the region level. Significantly different from zero at *10% significance, **5% significance level, ***1% significance level.

Table 5: Robustness for selection of countries and period

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Only Angola and Nigeria			Oil producing countries since 1959			Post 1973 period		
	Panel A. Period 1 (0-4 years old)								
	Education	Education	Education	Education	Education	Education	Education	Education	Education
	Full sample	Male sample	Female sample	Full sample	Male sample	Female sample	Full sample	Male sample	Female sample
Oil price shock × Oil Province	0.356***	0.214**	0.410***	0.265***	0.246***	0.258***	0.159*	0.209*	0.158*
	(0.115)	(0.103)	(0.126)	(0.088)	(0.093)	(0.094)	(0.086)	(0.107)	(0.088)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	134,846	37,911	96,935	237,383	49,328	188,055	479,319	114,876	364,441
Number of regions	55	55	55	108	81	108	247	220	247
R-squared	0.459	0.341	0.491	0.372	0.324	0.377	0.426	0.383	0.442
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B. Period 2 (5-9 years old)								
Oil price shock $_{O}ilProvince$	-0.180	-0.145	-0.173	-0.074	-0.087	-0.078	-0.553***	-0.057	-0.676***
	(0.117)	(0.132)	(0.126)	(0.090)	(0.122)	(0.095)	(0.180)	(0.202)	(0.181)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	134,846	37,911	96,935	237,383	49,328	188,055	479,319	114,876	364,441
Number of regions	55	55	55	108	81	108	247	220	247
R-squared	0.459	0.341	0.491	0.372	0.324	0.377	0.426	0.383	0.442
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Panel C. Period 3 (10-14 years old)								
Oil price shock $_{O}ilProvince$	-0.689***	-0.385***	-0.775***	-0.501***	-0.363***	-0.520***	-0.490***	-0.252	-0.556***
	(0.141)	(0.132)	(0.148)	(0.112)	(0.119)	(0.115)	(0.157)	(0.161)	(0.160)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	134,846	37,911	96,935	237,383	49,328	188,055	479,319	114,876	364,441
Number of regions	55	55	55	108	81	108	247	220	247
R-squared	0.459	0.341	0.491	0.372	0.324	0.377	0.426	0.383	0.442
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the years of education. Oil price shock is the ln-5 years average of oil price for period t multiplied by a dummy that take a value of 1 if the region is producing oil. Controls include year of survey, month of survey, religion, urban residency, and sex of household head. For the full sample, we control for gender. The method of estimation is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the region level. Significantly different from zero at *10% significance, **5% significance level, ***1% significance level.

Table 6: Sample restricted to at least 18 years old

	(1)	(2)	(3)
	Panel A. Period 1 (0-4 years old)		
	Education	**Education**	**Education**
	Full Sample	**Male sample**	**Female sample**
Oil price shock × Oil Province	0.147*	0.196**	0.136
	(0.081)	(0.094)	(0.087)
Controls	Yes	Yes	Yes
Number of observations	506,949	117,951	388,998
Number of regions	247	220	247
R-squared	0.427	0.395	0.436
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes
	Panel B. Period 2 (5-9 years old)		
Oil price shock × Oil Province	-0.009	0.083	-0.027
	(0.079)	(0.090)	(0.085)
Controls	Yes	Yes	Yes
Number of observations	506,949	117,951	388,998
Number of regions	247	220	247
R-squared	0.427	0.395	0.436
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes
	Panel C. Period 3 (10-14 years old)		
Oil price shock × Oil Province	-0.263***	-0.215*	-0.276***
	(0.088)	(0.123)	(0.092)
Controls	Yes	Yes	Yes
Number of observations	506,949	117,951	388,998
Number of regions	247	220	247
R-squared	0.427	0.395	0.436
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes

The dependent variable is the years of education. Oil price shock is the ln-5 years average of oil price for period t multiplied by a dummy that take a value of 1 if the region is producing oil. Controls include year of survey, month of survey, religion, urban residency, and sex of household head. For the full sample, we control for gender. The method of estimation is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the region level. Significantly different from zero at *10% significance, **5% significance level, ***1% significance level.

Table 7: Controlling for other minerals

	(1)	(2)	(3)
	Panel A. Period 1 (0-4 years old)		
	Education	**Education**	**Education**
	Full Sample	**Male sample**	**Female sample**
Oil price shock × Oil Province	0.190*	0.202**	0.184*
	(0.096)	(0.099)	(0.101)
Mineral price shock × Mineral Province	0.021***	0.013	0.011
	(0.007)	(0.011)	(0.009)
Controls	Yes	Yes	Yes
Number of observations	580,478	137,924	442,554
Number of regions	247	220	247
R-squared	0.420	0.387	0.431
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes
	Panel B. Period 2 (5-9 years old)		
Oil price shock × Oil Province	-0.084	0.057	-0.120
	(0.075)	(0.093)	(0.078)
Mineral price shock × Mineral Province	0.020**	0.014	0.011
	(0.008)	(0.011)	(0.009)
Controls	Yes	Yes	Yes
Number of observations	580,478	137,924	442,554
Number of regions	247	220	247
R-squared	0.431	0.420	0.387
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes
	Panel C. Period 3 (10-14 years old)		
Oil price shock × Oil Province	-0.397***	-0.238*	-0.436***
	(0.124)	(0.139)	(0.126)
Mineral price shock × Mineral Province	0.017**	0.013	0.008
	(0.008)	(0.012)	(0.010)
Controls	Yes	Yes	Yes
Number of observations	580,478	137,924	442,554
Number of regions	247	220	247
R-squared	0.420	0.387	0.431
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes

The dependent variable is the years of education. Oil price shock is the ln-5 years average of oil price for period t multiplied by a dummy that take a value of 1 if the region is producing oil. Mineral price shock is the ln-5 years average of mineral price for period t multiplied by a dummy that take a value of 1 if the region is producing a given mineral. Minerals included are gold, silver, aluminium, copper, lead, nickel, zinc and tin. Controls include year of survey, month of survey, religion, urban residency, and sex of household head. For the full sample, we control for gender. The method of estimation is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the region level. Significantly different from zero at *10% significance, **5% significance level, ***1% significance level.

Table 8: Other outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. Period 1 (0-4 years old)						
	Number of children	**Age at first marriage**	**Employed**	**Skilled occupation**	**Work all year**	**Husband's education**	**Husband's working**
	Female sample	**Female sample**	**Female sample**	**Female sample**	**Female sample**	**Female sample**	**Female sample**
Oil price shock × Oil Province	-0.124***	0.400***	0.008	0.006**	0.015**	0.015	0.018**
	(0.040)	(0.088)	(0.009)	(0.003)	(0.006)	(0.059)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	442,479	336,429	441,627	441,627	233,134	318,689	328,181
Number of regions	247	220	247	247	220	220	220
R-squared	0.589	0.242	0.264	0.050	0.199	0.393	0.222
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B. Period 2 (5-9 years old)						
Oil price shock × Oil Province	-0.068*	0.243***	-0.010	0.002	0.006	-0.015	-0.000
	(0.040)	(0.077)	(0.009)	(0.002)	(0.006)	(0.059)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	442,479	336,429	441,627	441,627	233,134	318,689	328,181
Number of regions	247	220	247	247	220	220	220
R-squared	0.589	0.242	0.264	0.050	0.199	0.393	0.222
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Panel C. Period 3 (10-14 years old)						
Oil price shock × Oil Province	0.121**	-0.274***	-0.017	-0.008*	-0.017*	-0.071	-0.031*
	(0.047)	(0.075)	(0.011)	(0.004)	(0.010)	(0.060)	(0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	442,479	336,429	441,627	441,627	233,134	318,689	328,181
Number of regions	247	220	247	247	220	220	220
R-squared	0.589	0.242	0.264	0.050	0.199	0.393	0.222
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Oil price shock is the ln-5 years average of oil price for period t multiplied by a dummy that take a value of 1 if the region is producing oil. Controls include year of survey, month of survey, religion, urban residency, and sex of household head. For the full sample, we control for gender. The method of estimation is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the region level. Significantly different from zero at *10% significance, **5% significance level, ***1% significance level.

Appendix

Table A1: Further robustness for selection of countries

	(1)	(2)	(3)	(4)	(5)	(6)
	Drop countries with only 1 oil region			Including non-oil producers		
	Panel A. Period 1 (0-4 years old)					
	Education	Education	Education	Education	Education	Education
	Full sample	Male sample	Female sample	Full sample	Male sample	Female sample
Oil price shock × Oil Province	0.198**	0.204*	0.204**	0.132	0.169*	0.131
	(0.097)	(0.105)	(0.103)	(0.090)	(0.087)	(0.095)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	430,541	99,387	331,154	1,122,325	291,450	830,872
Number of regions	177	150	177	462	435	462
R-squared	0.401	0.375	0.407	0.435	0.393	0.451
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B. Period 2 (5-9 years old)					
Oil price shock × Oil Province	-0.088	0.034	-0.106	-0.058	-0.029	-0.064
	(0.076)	(0.096)	(0.081)	(0.073)	(0.092)	(0.074)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	430,541	99,387	331,154	1,122,325	291,450	830,872
Number of regions	177	150	177	462	435	462
R-squared	0.401	0.375	0.407	0.435	0.393	0.451
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes	Yes	Yes	Yes
	Panel C. Period 3 (10-14 years old)					
Oil price shock × Oil Province	-0.414***	-0.270*	-0.446***	-0.278**	-0.289**	-0.288**
	(0.135)	(0.158)	(0.137)	(0.117)	(0.127)	(0.121)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	430,541	99,387	331,154	1,122,325	291,450	830,872
Number of regions	177	150	177	462	435	462
R-squared	0.401	0.375	0.407	0.435	0.393	0.451
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the years of education. Oil price shock is the ln-5 years average of oil price for period t multiplied by a dummy that take a value of 1 if the region is producing oil. Controls include year of survey, month of survey, religion, urban residency, and sex of household head. For the full sample, we control for gender. The method of estimation is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the region level. Significantly different from zero at *10% significance, **5% significance level, ***1% significance level.

Table A2: Controlling for migration

	(1)	(2)	(3)
	Panel A. Period 1 (0-4 years old)		
	Education	**Education**	**Education**
	Full Sample	**Male sample**	**Female sample**
Oil price shock × Oil Province	0.189*	0.202**	0.188*
	(0.098)	(0.099)	(0.103)
Oil price shock × Oil Province × Non-migrants	0.006	0.134	-0.014
	(0.046)	(0.205)	(0.050)
Controls	Yes	Yes	Yes
Number of observations	580,478	137,924	442,554
Number of regions	247	220	247
R-squared	0.420	0.387	0.431
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes
	Panel B. Period 2 (5-9 years old)		
Oil price shock × Oil Province	-0.085	0.056	-0.118
	(0.074)	(0.094)	(0.078)
Oil price shock × Oil Province × Non-migrants	0.005	0.148	-0.012
	(0.044)	(0.206)	(0.047)
Controls	Yes	Yes	Yes
Number of observations	580,478	137,924	442,554
Number of regions	247	220	247
R-squared	0.420	0.387	0.431
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes
	Panel C. Period 3 (10-14 years old)		
Oil price shock × Oil Province	-0.398***	-0.239*	-0.436***
	(0.124)	(0.139)	(0.126)
Oil price shock × Oil Province × Non-migrants	-0.010	0.109	-0.028
	(0.043)	(0.200)	(0.046)
Controls	Yes	Yes	Yes
Number of observations	580,478	137,924	442,554
Number of regions	247	220	247
R-squared	0.420	0.387	0.431
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes

The dependent variable is the years of education. Oil price shock is the ln-5 years average of oil price for period t multiplied by a dummy that take a value of 1 if the region is producing oil. Non-migrants is a dummy that takes the value of 1 if the respondant answered that he/she has been always residing in the place of residency. The dummy is also included on its own. Controls include year of survey, month of survey, religion, urban residency, and sex of household head. For the full sample, we control for gender. The method of estimation is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the region level. Significantly different from zero at *10% significance, **5% significance level, ***1% significance level.

Table A3: Controlling for first period shock

	(1)	(2)	(3)
	Period 3 (10-14 years old)		
	Education	**Education**	**Education**
	Full Sample	**Male sample**	**Female sample**
Oil price shock × Oil Province	-0.386***	-0.133	-0.450***
	(0.118)	(0.149)	(0.119)
Oil price shock × Oil Province in Period 1	0.016	0.141	-0.018
	(0.093)	(0.102)	(0.099)
Controls	Yes	Yes	Yes
Number of observations	580,478	137,924	442,554
Number of regions	247	247	220
R-squared	0.420	0.387	0.431
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes

The dependent variable is the number of years of education. Controls include year of survey, month of survey, religion, urban residency, and sex of household head. For the full sample, we control for gender. The method of estimation is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the region level. Significantly different from zero at *10% significance, **5% significance level, ***1% significance level.

Table A4: Robustness for wealth index - Adding more components

	(1)	(2)	(3)
	Panel A. Period 1 (0-4 years old)		
	Wealth	**Wealth**	**Wealth**
	Full Sample	**Male sample**	**Female sample**
Oil price shock × Oil Province	0.568**	0.883**	0.498*
	(0.278)	(0.382)	(0.294)
Controls	Yes	Yes	Yes
Number of observations	406,691	113,467	293,224
Number of regions	247	220	247
R-squared	0.437	0.432	0.441
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes
	Panel B. Period 2 (5-9 years old)		
Oil price shock × Oil Province	-0.084	0.177	-0.136
	(0.248)	(0.390)	(0.308)
Controls	Yes	Yes	Yes
Number of observations	406,691	113,467	293,224
Number of regions	247	220	247
R-squared	0.437	0.432	0.441
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes
	Panel C. Period 3 (10-14 years old)		
Oil price shock × Oil Province	-0.921***	-0.991**	-0.917**
	(0.349)	(0.439)	(0.357)
Controls	Yes	Yes	Yes
Number of observations	406,691	113,467	293,224
Number of regions	247	220	247
R-squared	0.437	0.432	0.441
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes

The dependent variable is the household wealth index constructed as explained in text. Oil price shock is the ln-5 years average of oil price for period t multiplied by a dummy that take a value of 1 if the region is producing oil. Controls include year of survey, month of survey, religion, urban residency, and sex of household head. For the full sample, we control for gender. The method of estimation is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the region level. Significantly different from zero at *10% significance, **5% significance level, ***1% significance level.

Table A5: Robustness for wealth index - Dropping components

	(1)	(2)	(3)
	Panel A. Period 1 (0-4 years old)		
	Wealth	**Wealth**	**Wealth**
	Full Sample	**Male sample**	**Female sample**
Oil price shock × Oil Province	0.648**	0.869**	0.587*
	(0.272)	(0.347)	(0.299)
Controls	Yes	Yes	Yes
Number of observations	466,754	129,652	337,102
Number of regions	247	220	247
R-squared	0.452	0.454	0.453
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes
	Panel B. Period 2 (5-9 years old)		
Oil price shock × Oil Province	0.026	0.177	-0.007
	(0.246)	(0.415)	(0.254)
Controls	Yes	Yes	Yes
Number of observations	466,754	129,652	337,102
Number of regions	247	220	247
R-squared	0.452	0.454	0.453
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes
	Panel C. Period 3 (10-14 years old)		
Oil price shock × Oil Province	-0.920***	-0.871**	-0.948***
	(0.318)	(0.428)	(0.336)
Controls	Yes	Yes	Yes
Number of observations	466,754	129,652	337,102
Number of regions	247	220	247
R-squared	0.452	0.454	0.453
Region FE	Yes	Yes	Yes
Age-interval FE	Yes	Yes	Yes
Region specific-time trend	Yes	Yes	Yes

The dependent variable is the household wealth index constructed as explained in text. Oil price shock is the ln-5 years average of oil price for period t multiplied by a dummy that take a value of 1 if the region is producing oil. Controls include year of survey, month of survey, religion, urban residency, and sex of household head. For the full sample, we control for gender. The method of estimation is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the region level. Significantly different from zero at *10% significance, **5% significance level, ***1% significance level.