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Abstract

In this paper, we study the impact of oil price shocks on the incidence of protest over the period 1991-2015. Our results indicate that negative oil price shocks are followed by an uptick in the number of protests and that a higher initial size of the shadow economy allows to mitigate the negative consequences of low oil prices on the likelihood of protest. To explain these results, we show that negative oil price shocks lead to a significant increase in the size of the shadow economy in highly oil dependent countries and that this countercyclical behavior is largely due to oil-price-driven income shocks. In our estimations, a decrease in the GDP per capita by one percentage point increases the shadow economy by 0.54 percentage points. This suggest that the shadow economy's capacity to absorb persistent oil price fluctuations without provoking political unrest, should regard it as a mitigation tool rather than an economic burden.

Keywords: Oil Price Shocks; Protest; Shadow Economy; Income

WORK IN PROGRESS

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I. Introduction

High oil export dependent countries are frequently subject to severe price swings that leave large impact on their macroeconomic fundamentals. Growth, fiscal position and social stability are affected by periods of (persistent) oil price booms and busts. With a special emphasis on oil producing countries, this paper explores the evolution of political instability – measured by the number of protests -- in reaction to oil price fluctuations and the mitigation role of the shadow economy.

For an oil-rentier economy, oil rents may create a cursory stability by building social bases whose support hinges upon the continuous availability of funds and the distribution networks (Beblawi and Luciani, 1987; Karl, 1997). Hence, during bust periods, the fall in revenues makes it quite difficult for the state to continue engaging in widespread distribution and so, inversely impacting household incomes benefiting from the distributional proceeds (e.g. subsidies, direct cash, public employment…etc.). Social unrest is then more likely with economic hardships lowering the opportunity cost for engaging in anti-state protests (i.e. grievances-driven). This was, for instance, evident in the social upheavals that broke out in Venezuela following the government's decision to cut the social subsidies amid the decline in oil prices.[2] Figure 1 presents a preliminary evidence of the relationship between international oil price movements and protest in a number of countries. It can be argued that periods of low oil prices have witnessed an uptick in the number of protests, and once oil prices has started to rise, the number of protests decline considerably.

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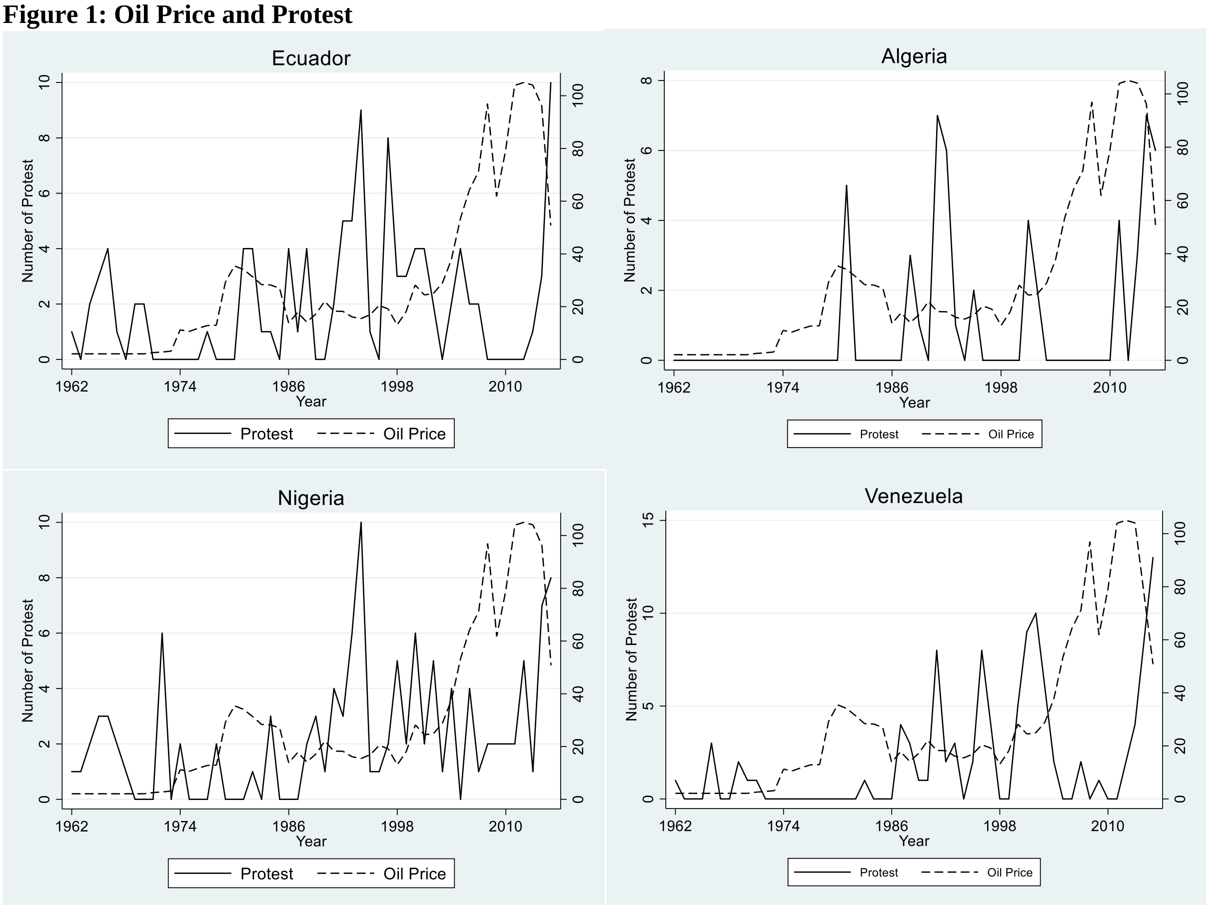
[2] See "https://edition.cnn.com/2017/04/21/americas/venezuela-crisis-explained/index.html"

Shadow economy might act as a countercyclical device to buffer against social unrest by providing an alternative source of income for the disgruntled citizens during economic downturns (e.g. Eilat and Zinnes, 2002; Boeri and Garibaldi, 2002; Dell'Anno and Solomon, 2007; Bajada and Schneider, 2009). As such, it acts as an insurance policy against unemployment through creating jobs and against economic stagnation through providing profit opportunities for business. In such setting, the existence of the shadow economy may increase the opportunity cost for protesting and allow governments to buy time. One could therefore expect oil price shocks to generate less social unrest in countries incubating big shadow economies.

Figure 1: Oil Price and Protest



In the context of oil producing countries, investigating the evolution of the shadow economy in reaction to oil price fluctuations and the implications for political stability is particularly appealing. This is true not only because of the vulnerability of those economies to export shocks, but also because of the considerable share of informal economies in their official GDP. According to the latest data from Medina and Schneider (2017), the percentage share of the shadow economy to GDP in oil producing countries ranges from 11 percent to 62 percent, with an average size of around 32 percent, which points to a significant role of the shadow economy in those economies. However, the mitigation role of the shadow economy is contingent upon its countercyclical response to negative oil price shocks and their subsequent impact on the official economy growth. In other words, the size of shadow economy should remain resilient to oil-induced growth shocks. This comes in contrast with the competing view of the procyclical relationship between the official economy's growth and the expansion of the shadow economy (e.g. Giles, 1997a; 1997b; 1999; Giles and Tedds, 2002; Bajada, 2003). That is, a slowdown the official GDP growth rate drives down the size of the shadow economy.

Utilizing a natural experiment context, our empirical strategy starts by investigating how fluctuations in international oil prices mobilize social unrest. We look, in particular, at less severe incidences of instabilities, namely protest, which remains less studied compared to more violent events of civil wars and regime breakdowns. Our exogenous measure for oil revenues is based on the variation in international oil prices weighted by time-invariant country's oil exports share to GDP. This allows circumventing the problems associated with conventional measures of resource abundance measured in terms of the values of oil production or as the share of resource rents in GDP. We, then, investigate whether a higher size of shadow economy can mitigate the adverse impact of oil price shocks on social unrest. To explain our findings, we move to studying the impact of exogenous oil price shocks on shadow economy in a broader set of countries and using within-country variation. Finally, to examine whether the shadow economy responds to a growth shock in a pro-cyclical or counter-cyclical manner, we apply an instrumental variables approach using oil price shocks as an instrument. This aims at avoiding problems of endogeneity associated with modelling the impact of growth shocks on shadow economy activities. Several robustness checks and modifications should help to support the validity of the exogeneity assumptions.

To do so, we use a panel dataset on incidences of protest and index for oil price shocks in 184 countries during the period 1991-2015. Our findings point out that negative oil price shocks are followed by uptick in the number of protests and that the effect is more severe the lower the initial level of the shadow economy. This works through the countercyclical reaction of the shadow economy to oil price shocks. Our results indicate that negative income shocks have a positive and significant impact on the size of the shadow economy. In highly oil dependent countries, a 10 percentage point drop in international oil prices increases the shadow economy on impact by 0.26 percentage point for each 10 percentage point increase in oil exports over GDP. We find that oil-price-driven income shocks explain countercyclical behavior to a large extent. In particular, a one percentage point increase in the GDP per capita increases the shadow economy by 0.54 percentage points. The results suggest an ambiguity in the role of the shadow economy. For highly resource dependent countries, the shadow economy sector might serve as an important social risk management device. For the planning and conceptualization of reforms policymakers should take this into account. The capacity to absorb persistent oil price fluctuations without political unrest, should present the shadow economy as a mitigation tool rather than an economic burden.

This paper contributes to the literature in three dimensions. First, our study is related to the literature on the positive association between economic shocks and civil conflict driven by deepened economic grievances and weakened state capacity to buy off political opposition (e.g. Collier and Hoeffler, 1998; Fearon and Latini, 2003; Miguel, Sctyanath and Sergenti, 2004; Ross, 2004; Brückner and Ciccone, 2010; Besley and Persson, 2011; Hendrix and Salehyan, 2012; Dube and Vargas, 2013; Lei and Michaels, 2014). Closely related is the literature on relative deprivation (Gurr, 1968) which states that feelings of deprivation are likely to arise not only from intergroup comparisons, but also from intrapersonal comparisons of past welfare. More broadly, an important strand of literature emphasizes the role played by natural resources, particularly oil and mineral rents, in enhancing civil conflicts through either funding rebel organizations (i.e. greed-driven conflicts) or fueling discontent over the unequal distribution of income (i.e. grievance-driven conflicts) (Bannon & Collier, 1999; de Soysa, 2002; Lujala, 2009; Wantchekon, 2002; Collier and Hoeffler, 2004). In contrast to these studies, we estimate the effect of economic shocks on less violent incidences of social unrest (i.e. protests) which remains largely unexplored coupled with the recent findings of Bazzi and Blattman (2014) showing oil price shocks to be not associated with wars outbreaks, but with shorter less intense civil conflicts. To the best of our knowledge, there is only the study of Smith (2004) that examines the impact of oil price shocks on anti-state protest and finds that oil wealth is associated with fewer protests, even if some oil states have witnessed some protest during the bust period. This study, however, is based on a cross-country empirical specification, which makes it difficult to make causal inferences. Furthermore, the measure of the time-varying value of oil exports to GDP is partly based on oil production. This in turn makes it endogenous to social unrest.[3] Second, there is a very little empirical evidence for the mitigation role of the shadow economy on social unrest in the context of economic shocks.[4] We find a beneficial role of a countercyclical reacting shadow economy in soothing protests breakout, providing a counter argument for existing literature showing countercylicality to exhibit negative impacts during bust periods through reducing tax bases and deepening economic stagnation (Elgin, 2012).

Third, our work contributes to the empirical studies on the reaction of the shadow economy to growth cycles, in which there have been little consensus on whether shadow economy behaves in a pro- or countercyclical manner. Some country specific studies refer to the negative association between the size of shadow economy and the official economy, and find unemployment to be the main driver of shadow economy (e.g. Dobre and Alexandra, 2009; Dell'Anno et al., 2007; Elgin, 2012; Schneider and Humetner, 2014; Bitzenis, Valchos and Schneider, 2016). Other studies emphasize the conditional response of underground economy. For instance, according to Loayza and Rigolini (2011), the informal unemployment appears to be countercyclical in the short run, but the degree of countercyclicality is rather decreasing with its size. In the same rein, Bajada and Schneider (2009) point out to the existence of a pro-cyclical relationship in Australia, Italy, and New Zealand due to the transitory effects of unemployment changes on participation in the shadow economy. However, none of these studies identifies the source of growth shocks and none succeeds in addressing endogeneity problems associated with examining the response of the shadow economy to economic growth cycles. In contrast, we focus on a particular type of economic shocks (international oil price shocks) to establish a source of exogenous variation and use that as instrument for business cycles. As such, we make use of a natural experiment framework that

[3] Other authors have looked at the effects of rising food prices on social unrest and mostly pointed to a strong positive relationship (Berazneva and Lee, 2013; Smith, 2014; Weinberg and Bakker 2014). Such relationship was also found to be rather conditional on the degree of the development of the country (i.e. low income vs. high-income countries) (Arezki and Brückner, 2011) or on the type of the political system (democracy vs. autocracy) (Hendrix and Haggard, 2015). In a more comprehensive study, Bazzi and Blattman (2014) find no evidence of an impact of high commodity price shocks on the onset of new civil wars.

[4] The literature on the shadow economy is so far either focusing on estimating its size and discerning its causes (e.g. Schneider and Enste, 2000) or studying its impact on official economy and vice-versa on either limited subset of countries or using cross-country variation (e.g. Dell'Anno, 2008; Tedds and Schneider, 2002). Other cross-country studies examined its relationship with other macroeconomic variables such inequality and corruption (e.g. Dreher and Schneider, 2010; Dell'Anno, 2016).

allows us to make progress towards previous literature by examining the direct impact of oil price shocks on the shadow economy and discerning the mechanism behind that impact.

The remainder of the paper is organized as follows. Sections 2 and 3 describe our data and empirical methodology. Sections 5, 6 and 7 present our main findings and robustness checks; and section 8 concludes with a broader discussion of the results and providing policy implications.

II. Data

Our panel dataset combines information on oil price shocks, shadow economy and protest over the period 1991 to 2015. The country-specific measure of annual oil price shocks for country i at time t is constructed by multiplying the time-invariant whole-period average of country i's share of oil exports to GDP δ_i with the annual ln-change in international oil prices $\Delta \ln OilPrice_t$ and takes the following form:

$$OilPriceShock_{it} = \delta_i \, \Delta \ln OilPrice_t$$

This specification captures that oil price shocks should have a greater impact on countries with greater dependence on oil. The oil exports data are from the United Nations' Comtrade data set reported according to the SITC1 system. Missing data are either replaced by numbers from IMF's World Economic Outlook Database or by zeros if the country does not produce oil, as reported by Energy Information Administration (EIA). Data on international oil prices are taken from United Nations Conference on Trade and Development Commodity Statistics (UNCTAD, 2016).[5] The calculated country's share of oil to GDP δ_i is revised so that extreme values, presenting more than 150 percent of GDP were replaced by the second highest value to avoid some of the problems associated with the reported export values that may be inaccurate for specific countries (Feenstra et al., 2005).[6]

To measure the shadow economy, we rely on the data taken from Medina and Schneider (2017), who define the shadow economy as "all the economic activities hidden from official authorities to avoid paying taxes and all social security contributions, to avoid governmental bureaucracy or the burden of regulatory framework, and for institutional reasons including corruption law, the quality of political institutions and weak rule of law". Their dataset covers the shadow economic activities in 158 countries during the period from 1991 to 2015. The estimates for the size of the shadow economy, measured as a percentage of GDP, are based on the Multiple Indicators Multiple Causes (MIMIC) model. This empirical approach first treats the shadow economy as an unobserved (latent) variable, identifying multiple causes and indicators for estimating its size. Second, it uses structural equations model to estimate the causal relationships between the unobserved variable and the observed indicators. A key advantage of this dataset is that it uses a light intensity approach instead of GDP as an indicator variable, and hence, avoiding the criticism often raised due to the use of GDP per capita (or the growth rate of GDP per capita) as both cause and indicator variables. A second advantage of this dataset is having a longer time span compared to the most widely used dataset by Schneider, Buehn, and Montenegro (2010) covering a relatively limited period from 1999

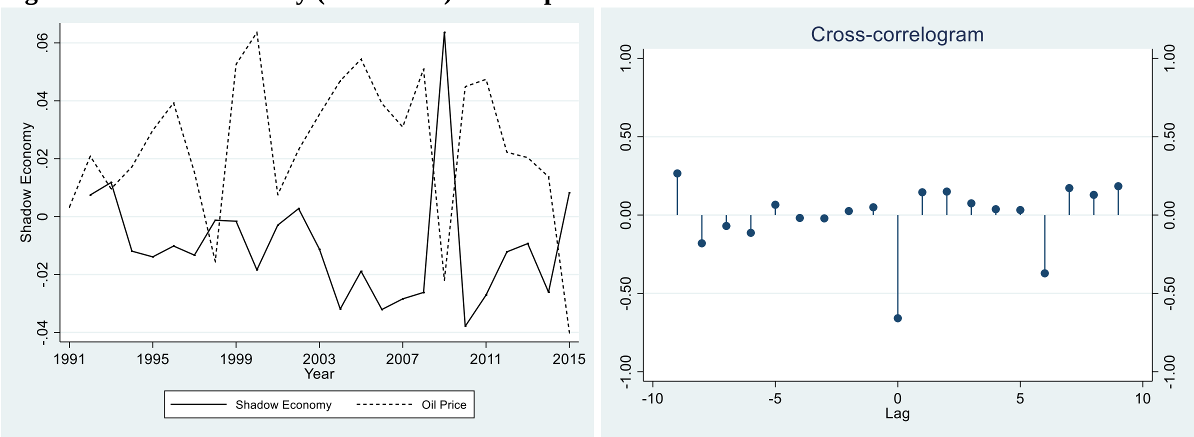
[5] The correlation between the original series and the filled-in series is 100 percent. In the online appendix, we check the robustness of our results by removing all the IMF data and the results remain robust.

[6] Only 9 observation were modified for The Bahamas (1975-1982), Oman (1970-1971) and Qatar (1971-1972).

to 2007. Our measure of GDP growth is calculated using data on real GDP per capita from World Development Indicators (World Bank, 2018).

To get a first snap shot of the relationship between oil price shocks, and the size of the shadow economy as a percentage of GDP. Figure 5 (a) depicts the growth of shadow economy and the annual change in oil price and shows a negative correlation between them. To gauge more on the strength and the timing of such correlation, in Figure 5 (b), we plot the cross-correlogram between the growth in the shadow economy and oil price changes at different leads and lags. The strongest cross-correlation happens at lag zero with a negative sign indicating that an above average increase of oil prices is associated with an immediate below average growth of the shadow economy and the opposite is true. A below average increase in oil prices is more likely to be associated with an above average growth of the shadow economy on impact, suggesting a countercyclical response of shadow economy to oil price shocks.

Figure 5: Shadow economy (% of GDP) and oil price



Note: Figure 5(a) displays the growth in the (log) size of shadow economy (% of GDP) (solid line) averaged across the sampled countries along with the ln-change in oil price (dashed line). Figure 5(b) displays the cross-correlograms between the growth in the shadow economy and ln-change in oil price.

We rely on the data from Cross-National Time-Series Data Archive (CNTS) (Banks, 2018) to construct our indicators for protest. The CNTS dataset measures different types of political instabilities ranging from less intense incidences of protests to major events of civil wars and coups. Given the purpose of this paper, we only select 3 indicators for less violent events of instabilities, namely anti-government demonstrations, general strikes and riots. We construct two measures for protest. The first is a binary variable that takes the value of one if any protest event took place in a given year and zero otherwise. We call this variable, $Protest\ binary$. The second indicator, $Protest\ count$, (expressed in logs) is a count variable calculated by summing the numbers of all demonstrations, strikes and riots that took place in a given country at a given year; hence, it captures the magnitude or the intensity of instability.

Table 1: Summary Statistics

Variable	N	Mean	SD	Min	Max
Oil price shock	3407	0.003	0.04	-0.42	0.29
Shadow Economy (% of GDP)	3407	31.42	12.88	6.16	71.95
Shadow Economy (% of GDP) (log)	3407	3.35	0.48	1.82	4.28
GDP per capita (log)	3338	8.34	1.60	4.75	11.63
Protest	3407	1.62	5.88	0	144

III. Empirical Specification

Our empirical strategy assesses whether changes in international oil prices affect incidence of protest disproportionately in countries that depend more on oil. Specifically, we estimate:

$$Protest_{it} = \alpha_{pi} + \gamma_{pi}t + \beta_{p1}OilPriceShock_{it} + \beta_{p2}SE_{it-1} + \beta_{p3}OilPriceShock_{it} \times SE_{it-1} + \varepsilon_{pit} \quad (1)$$

The dependent variable $Protest_{it}$ is one of the two measures of protest events in a given country i and year t, α_{pi} is country fixed effects, and ε_{pit} is the error term. $OilPriceShock_{it}$ is the explanatory variable of interest measured as the change in oil prices, averaged over the previous three years. This allows us to take into account the time-dependence of shocks, with the current shock being correlated with previous shocks, besides reducing the role of transitory shocks and measurement error in the explanatory variable.[7] To investigate the mitigation role of the shadow economy for the adverse effects of oil price shocks on protest, we add the lagged value of the shadow economy SE_{it-1}, both by itself and interacted with oil price shocks. This allows us to examine the impact of oil price shocks on protest conditional upon the initial size of the shadow economy. If the shadow economy mitigates adverse shocks, we shall expect negative oil price shocks to have a smaller effect on protest in countries with a relatively higher size of the shadow economy. To be consistent with the starting date of the price shock and to address reverse causality, the initial size of the shadow economy is measured with a one-year lag. Hence, if the change in oil prices is measured as the average over the years t, $t-1$, $t-2$ and $t-3$ the size of shadow economy enters at year $t-4$.[8] $\gamma_{pi}t$ is a country-specific linear time trend to account for potential omitted variables and pre-existing trends. For instance, high oil dependent countries may be more prone to social unrest for reasons related to income inequality or non-cohesive state institutions. To address that, one approach is to include a country-specific tend, by adding a linear time trend and interacting each of the time-invariant country-specific characteristics with this time trend. In this way, the pre-existing trends can be absorbed without biasing our estimates and a possible omitted variable bias is reduced. Another approach can be through including time-fixed effects, to remove any general association between oil price and protest in a given year. However, our measure of the shadow economy is subject to measurement error and adding additional year fixed-effects can bias the estimates towards zero. Furthermore, shadow economy has a relatively low within-standard deviation of 0.55 compared to a mean of 22.7.

For the specification with the dependent variable, $Protest\ count$, the method of estimation is ordinary least squares. With the dependent variable, $Protest\ Binary$, equation (3) is estimated using both fixed effects linear probability model, which is similar to a fixed effect OLS model for limited dependent variables, and conditional fixed effect logit models.

[7] This is same approach followed by Brückner and Ciccone (2010), Brückner, Ciccone and Tesei (2012) and Caselli and Tesei (2016). In the online appendix, we show that indeed oil price shocks are serially correlated.

[8] We also considered going beyond the fourth lag, when choosing the initial level of the shadow economy. However, deeper lags severely reduces our sample size. Furthermore, as previously shown the shadow economy is left unaffected by lagged oil price shocks (beyond year t) which suggested that a lagged level of the shadow economy can be treated as a predertmined variable, whose lagged values are uncorrelated with the current error term.

Second, to examine whether changes in international oil prices affect the size of the shadow economy disproportionately in countries that produce more oil. The within-country specification takes the following form:

$$\Delta SE_{it} = \alpha_{si} + \gamma_{si}t + \beta_s OilPriceShock_{it} + \varepsilon_{sit} \quad (2)$$

where α_{si} is country fixed effects and ε_{sit} is the error term. We measure the shadow economy growth ΔSE_{it} as either the change in the size of the (log) shadow economy between $t-1$ and t or its (log) business cycle component generated by the Hodrick–Prescott (HP) filter.[9] $\gamma_{si}t$ is a country-specific linear time trend to mitigate potential omitted variable bias. For instance, high oil-dependence may be correlated with corruption and the latter is correlated with more shadow economy presence. The method of estimation is ordinary least squares. Adding year-fixed effects is not preferred, given the same reasons noted above. Third, to examine whether the shadow economy responds in pro- or countercyclical fashion to official economy growth shocks, we estimate a two-stage least squares (2SLS) model:

$$\Delta SE_{it} = \alpha_{ci} + \gamma_{ci}t + \beta_c \Delta logGDP_{it} + \varepsilon_{cit} \quad (3)$$

where α_{ci} is country fixed effects, $\gamma_{ci}t$ is a country-specific linear time trend and ε_{cit} is the error term. $\Delta logGDP_{cit}$ is either the change in (log) real per capita GDP or its (log) business cycle component generated by (HP) filter, and it is instrumented by oil price shocks. Hence, an advantage of applying this approach is that it helps to circumvent endogeneity problems associated with modelling the impact of growth on the expansion of underground activities.[10] For the instrumental variable approach to be valid, oil price shocks must satisfy two conditions: (i) the independence condition requiring the instrument not to be determined by the outcome variable and (ii) the exclusion restriction. In our case, the occurrence of oil price shocks cannot be a function of the growth in the shadow economy. The corresponding exclusion restriction in equation (3) requires that oil price shocks affect the size of the size economy only through income. Focusing, however, on income as specific channel of causation makes our analysis silent on other possible channels through which oil price shocks affects the shadow economy (e.g. tax burden, unemployment, political instability, corruption…etc.). The next section provide evidence of the dominance effect of the income channel over other mechanisms.

IV. Empirical Results

(a) Oil price shocks and protest

In Table 2, we examine whether the impact of oil price shocks on the level of protest is decreasing, the higher the initial level of the shadow economy using equation (1). As previously discussed, we use two measures for protest: a count indicator to capture the intensity of ongoing protests and the binary indicator to capture the likelihood (probability) that a protest even would take place in a given country at a given year. Columns 1-3 consider the effect of oil price shock and the initial level of the shadow economy on the intensity of protest measured by the change in the (log) number of protests. In column 1, the negative

[9] Because of our relatively short time-series, we prefer Hodrick–Prescott (HP) filter over other business cycle (frequency) filters (e.g. Baxter and King, 1999) to reduce the entailed loss of observations.

[10] Instrumenting GDP by oil-price shocks is used by Brückner, Ciconne anf Tesei (2012) in studying the impact of income shocks on regime change. However, our measure for oil price shocks differ from theirs, since our measure is weighted by the whole-period average oil exports over GDP, whereas their measure uses the whole-period average of net oil exports over GDP.

statistically significant estimate imply that negative oil price shocks lead to a significant increase in the number of witnessed protests at 10 percent significance level, aligned with the grievances and the opportunity cost mechanism predicting a negative relationship between adverse economic shocks and political dissent. Column 2 adds the four-year lagged level of the shadow economy (% of GDP), both by itself and interacted with the 3-year average oil price shock, as additional control variables. We still find that a negative oil price shock significantly increases the number of protests, while a higher size of the shadow economy significantly reduces the number of protest at 5 percent significance level. The interaction term between oil price shocks and the lagged shadow economy is positive and statistically significant indicating that the effect of negative oil price shocks on protest is less severe in countries with higher initial size of the shadow economy. Since the impact of oil price shocks on the incidence of protest can differ depending past history of protest breakouts, we add in column 3 two additional control variables: an indicator for number of previous protest incidences (*past protest*) and a count variable for the length of time it took for a new incidence to take place (*Duration*). The effect of our main variable of interests remains statistically significant. The point estimate in column 3 implies that a 10 percentage point drop in international oil prices leads, on average, to an increase in the number of protests of about 6.6 percentage points for each 10 percentage point increase in oil exports over GDP and the effect is statistically significant at 1 percent significance level.[11] The statistically significant estimate of the shadow economy indicate that a 10 percentage point increase in shadow economy lead to a 0.1 percentage point decline in the number of protest breakouts.

Table 2: Oil price shocks, protest and shadow economy

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Δ Protest Count	Δ Protest Count	Δ Protest Count	Protest Binary	Protest Binary	Protest Binary	Protest Binary	Protest Binary	Protest Binary
	OLS	OLS	OLS	OLS	OLS	OLS	FE Logit	FE Logit	FE Logit
3-year average oil price shock, *t*	-0.569*	-4.560***	-6.588***	-1.611***	-2.694**	-3.465***	-11.494***	-19.907**	-18.095**
	(0.312)	(1.420)	(1.576)	(0.328)	(1.078)	(1.100)	(3.077)	(8.989)	(8.903)
Shadow economy (level), *t-4*		-0.014**	-0.014**		-0.012***	-0.007**		-0.123***	-0.116***
		(0.005)	(0.006)		(0.004)	(0.004)		(0.014)	(0.016)
3-year average oil price shock*Shadow economy (level)		0.122***	0.130***		0.037	0.051		0.244	0.233
		(0.037)	(0.048)		(0.030)	(0.031)		(0.256)	(0.253)
Past protest			-0.207***			-0.185***			-0.007
			(0.026)			(0.022)			(0.021)
Duration (log)			0.316***			-0.111***			-0.408***
			(0.025)			(0.018)			(0.057)
Number of observations	3,563	3,270	3,270	3,563	3,270	3,270	3,336	3,041	3,041
Number of countries	156	156	156	156	156	156	146	145	145
log-likelihood							-1464	-1281	-1254
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country specific-time trend	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No

3-year average oil price shock is the average three year ln-change in the oil price multiplied by whole period average oil exports share to GDP (1991-2015). The method of estimation in columns 1-6 is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the country level; in columns 7-9 is conditional fixed effects logit model. The dependent variable *Protest binary*is a binary variable that takes the value of one if any protest event took place in a given year and country and zero otherwise; *Protest count*, is the (log) of sum of protest events that took place in a given country at a given year. Country fixed effects and country-specific time trend are not reported. Significantly different from zero at *90% confidence, **95% confidence, ***99% confidence.

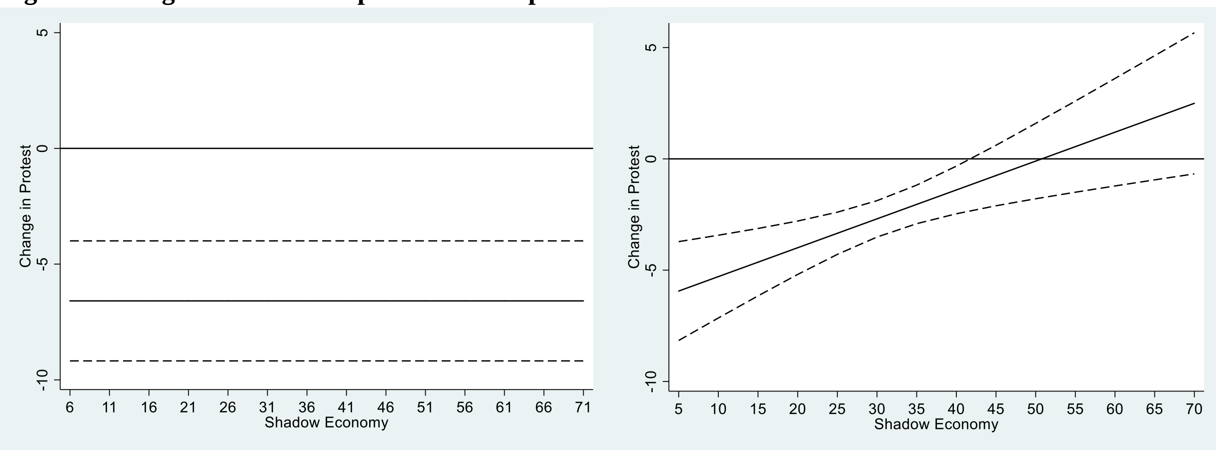
Columns 4-6 estimates equation (1) using a linear probability model. Throughout the models, we find that a negative oil price shock still significantly increases the likelihood of witnessing protests, while a higher size of the shadow economy significantly reduces the likelihood of protest breakout at 1 percent significance level. In columns 7-9, we perform the same analysis on the binary indicator, but estimate equation (1) using conditional fixed effects logit model. Because the logit estimators do not converge

[11] The estimated effect is calculated by multiplying the coefficient by the square of 0.1.

when a country-specific time trend is included, this term is omitted from the logit analysis. In all specifications, the statistical significance of the estimates point to an inverse relationship between negative oil price shocks and protest. That is, periods with lower oil prices experience a higher likelihood of witnessing protests. The effect of the shadow economy on the likelihood of protest remains as well negative and statistically significant. In both models, however, the interaction term between oil price shock and initial size of the shadow economy (i.e. conditioning variable) is positive, but statistically insignificant.

Given the little difference in results between the estimated models, we prefer the protest intensity models over the others to simplify interpretation of the coefficients and allowing us to include country-specific time trends. Based on column 3, we estimate the marginal effects of oil price shocks on the change in the number of protest at different levels of the shadow economy. Our main results are illustrated in figure 2, plotting the estimated effect conditional upon the initial level of the shadow economy, along with 90 percent confidence bands. In the left plot, we have the average linear (unconditional) effect which negative and statistically significant at all initial levels of the shadow economy. In the right plot, we report the conditional effect and see that the negative impact of oil price shocks is more severe the lower the initial level of the shadow economy.[12] The estimated coefficients imply that the impact of negative oil price shocks on protest in low shadow economy countries (at 10% of GDP) is almost four times severe as that in high shadow economy countries (at 40% of GDP). For instance, a 10 percentage point decline in oil prices increase the probability of witnessing protest by 5.3 percentage point in a low shadow economy country compared to 1.4 percentage point increase in a high shadow economy country.

Figure 2: Marginal effect of oil price shock on protest



Note: Figure 2(a) displays the linear (unconditional) effect of oil price shocks on the change in the number of protest at different levels of initial shadow economy. Figure 2(b) displays marginal effects of oil price shocks on the change in the number of protest at different levels of initial shadow economy.

Other results based on column 3 indicate that a negative statistical significant effect of the past history of protest and that longer the time lapse between two subsequent protest events are associated with more protests. Given that both coefficients are not robust to different estimations, their interpreted impact should be taken with caution. One interpretation could be that public experience with protest has a negative impact on their future decisions to participate due to the inability of past protests to achieve its

[12] The same results can be also obtained using linear probability models or conditional fixed-effect logit (columns 3 and 8).

goals (e.g. to cause a policy change) or for a fear of a repressive response from the authorities. Furthermore, the longer the time span between two protest events, the more likely for protests to take place.

One important concern with our estimates is that our measure for oil price shocks may be correlated with pre-existing trends in the outcome of interest. For instance, oil dependent countries could be systematically different from non-oil counterparts or within themselves for reasons related to geography, population, economic growth, inequality…etc, making our oil shock variable correlated with other covariates. For this reason, we included in all specifications a country-specific linear time trend to rule out that the estimated effects are simply driven by the correlation between pre-existing trends and future price shocks. We corroborate this by performing a falsification test in table 3 through relating future oil price shocks to protest incidences between 1966 and 1990 (i.e. the 25 years before the start of our period of analysis). The results show oil price shocks are uncorrelated with pre-trends in protest incidences. In other words, the past protest events do not vary with change in international oil prices that will later take place. In all specifications, the coefficients are smaller in magnitude compared to our baseline results table 2.[13]

Table 3: Oil price shocks and protest (1966-1990) - falsification test

Model	(1)	(2)	(3)
	Protest Binary (1966-1990)	Δ Protest Count (1966-1990)	Protest Binary (1966-1990)
	OLS	OLS	FE Logit
3-year average oil price shock, *t*	-0.214	-0.231	-2.633
	(0.385)	(0.355)	(4.152)
Number of observations	3,563	3,563	2,599
Number of countries	156	156	113
log-likelihood			-999.8
Country FE	Yes	Yes	Yes
Country specific-time trend	Yes	Yes	No

3-year average oil price shock is the average three year ln-change in the oil price multiplied by whole period average oil exports share to GDP (1991-2015). The method of estimation in columns 1 and 2 is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the country level; in column 3 is conditional fixed effects logit model. The dependent variable *Protest binary* is a binary variable that takes the value of one if any protest event took place in a given year and country and zero otherwise; *Protest count*, is the (log) of sum of protest events that took place in a given country at a given year. Country fixed effects and country-specific time trend are not reported. Significantly different from zero at *90% confidence, **95% confidence, ***99% confidence.

In the online appendix, we conduct additional robustness checks. In table A1, we investigate the heterogeneity of the effects between autocratic and democratic regimes by including a dummy variable that is equal to 1 if the country is democratic at $t-4$. The democracy dummy enters both on its own, and interacted with oil price and the initial level of the shadow economy in a triple-interaction-term manner. We base our classification for political regimes on the Polity IV regime database (Marshall and Jaggers, 2016) and follow the convention of classifying countries as democracies, if their polity2 score is strictly positive (e.g. Persson and Tabellini, 2009; Caselli and Tesei, 2016).[14] Although the point estimates indicate that democracies witness, on average, more protest following negative oil price shocks and that the effect becomes smaller the higher the initial level of the shadow economy, but the results are statistically insignificant. In table A2, we check our results after excluding major oil producers and OPEC

[13] It should be noted that some countries did not exist before 1991 and therefore, we replaced protest events in those countries by zero to reduce selection bias issues and keep the sample size the same. Results remain unchanged, if we dropped those countries (results available upon request).

[14] Following Brückner and Ciccone (2011), we adjust Polity2 so that periods of interregnum, coded as 0, and transitionary periods are treated as missing. Such adjustment ensure that instability are not affected by the particular political situation in a given year. The results also remain robust to including those periods.

countries. One concern is that the international price of oil could be endogenous to major oil producers introducing bias to the estimates. Specifically, reverse causality may arise if an intensification of protest lowers oil production levels, causing the international prices to increase. The baseline results remain robust to these exclusions.

(b) Oil price shocks and the shadow economy

In the previous section, we report that the effect of oil price shocks on the incidence of protest becomes smaller the higher the initial size of the shadow economy. To explain these results, Table 4 presents our main empirical results of the effect of oil price shocks on the shadow economy growth. Columns 1 and 2 shows that a negative oil price shock in t is followed by a statistically significant increase in the shadow economy at 1 percent significance level. In particular, the statistically significant point estimate in column 2 implies that a 10 percentage point drop in international oil prices increases the shadow economy by 0.26 percentage point for each 10 percentage point increase in oil exports over GDP. In column 3, we look at the average impact of oil price shocks in $t-1$ on the shadow economy and find a negative, but statistically insignificant effect. Hence, in line with our finding in section 2, the strongest significant impact of oil price shocks on shadow economy occurs contemporaneously.[15] Columns 4-5 estimate the effect of oil price shocks on the growth cycles of the shadow economy (i.e. the business-cycle component generated by HP filter). We obtain exactly the same results as in columns 1-3. Based on column 4, the effect of a negative oil price shock on the shadow economy is positive and statistically significant at 1 percent significance level. To gauge the magnitude of the effect, 10 percentage point drop in international oil prices increases the shadow economy by 0.15 percentage point for each 10 percentage point increase in oil exports over GDP.

Table 4: Oil price shocks and the shadow economy

Model	(1)	(2)	(3)	(4)	(5)
	Δ SE	Δ logSE	Δ logSE	logBC-SE	logBC-SE
	OLS	OLS	OLS	OLS	OLS
3-year average oil price shock, *t*	-7.993*** (2.541)	-0.262*** (0.081)		-0.146*** (0.030)	
3-year average oil price shock, *t-1*			0.017 (0.061)		-0.042 (0.027)
Number of observations	3,563	3,563	3,407	3,563	3,407
Number of countries	156	156	156	156	156
Country FE	Yes	Yes	Yes	Yes	Yes
Country specific-time trend	Yes	Yes	Yes	Yes	Yes

The dependent variable in column 1 is the change in the size of the shadow economy as a percentage of GDP; in columns 2 and 3 is the change in the (log) size of the shadow economy as a percentage of GDP; in columns 4 and 5 is the log business-cycle component of the log-shadow economy generated by HP filter. 3-year average oil price shock is the average three year ln-change in the oil price multiplied by whole period average oil exports share to GDP (1991-2015). The method of estimation is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the country level. Country fixed effects and country-specific time trend are not reported. Significantly different from zero at *90% confidence, **95% confidence, ***99% confidence.

To test whether the impact of oil price shocks on shadow economy is driven by the official economy growth, oil price shocks should have a significant effect on GDP as pre-condition. Table 5 contains the estimates of the effect of the 3-year average oil price shock on (log) real GDP per capita growth. Column 1 shows that the effect of contemporaneous oil price shock on GDP per capita is positive and statistically significant at 1 percent significance level. The results indicate that a 10 percentage point increase (decrease) in international oil prices increases (decreases) GDP per capita by 0.53 percentage points for

[15] In unreported results, we find that the lagged oil price shocks, measured by the lagged 3-year average shock, in periods $t-1, t-2$ and $t-3$ have insignificant effect on the current shadow economy (results available upon request).

each 10 percentage point increase in oil exports over GDP. In column 2, we look at the effect of oil price shocks on the growth cycle of (log) real GDP per capita generated by HP filter. We find that a 10 percentage point increase (decrease) in international oil prices increases (decreases) GDP per capita by 0.19 percentage points for each 10 percentage point increase in oil exports over GDP. The results come in line with Brückner, Ciconne and Tesei (2012) who find positive oil price shocks to have a positive and persistent effect on GDP per capita growth. Hence, combined with our findings in table 2, oil price shocks have a contemporaneous effect GDP per capita, which immediately affects shadow economy at period t.

Table 5: Oil price shocks and GDP per capita

Model	(1)	(2)
	Δ logGDP	**logBC-GDP**
	OLS	**OLS**
3-year average oil price shock, *t*	0.537*** (0.118)	0.187*** (0.029)
Number of observations	3,469	3,482
Number of countries	155	155
Country FE	Yes	Yes
Country specific-time trend	Yes	Yes

The dependent variable in column 1 is the change in (log) real GDP per capita; in column 2 is the log business-cycle component of (log) real GDP per capita generated by HP filter. 3-year average oil price shock is the average three year ln-change in the oil price multiplied by whole period average oil exports share to GDP (1991-2015). The method of estimation is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the country level. Country fixed effects are not reported. Significantly different from zero at *90% confidence, **95% confidence, ***99% confidence.

Furthermore, one of the main conditions for the validation of our empirical strategy is that oil price shocks do not affect shadow economy through other channels other than the official GDP. Support for this claim is based on showing that oil price shocks has little or no effect on the drivers of the shadow economy and that the income effect is dominant over other mechanisms. In the shadow economy literature, high tax burden, extensive regulations and corruption are widely established as potential drivers for underground economy (Dreher and Schneider, 2010). During economic downturns, a substitution effect stemming from the shift of the unemployed from the stagnated official economy affects the shadow economy (Bajada and Schneider, 2009). Hence, unemployment casts its effect on the proliferation of non-official economy over growth cycles. Poor educational attainment can affect directly the shadow economy, since low-skilled worker have lower chance to find a job in the official economy (Berrittella, 2015). Finally, political instability can cause governments to choose policies that allow the informal economy to develop. For instance, political uncertainties may reduce state incentives to reform tax regulations, opening doors for more informal activities (Elbahnasawy, Ellis and Adom 2016).

We have previously reported that oil prices significantly affect the degree of political stability measured by the level of protest. In Table 6, we examine how oil price shocks affect other potential drivers. All left hand side variables are transformed using the natural logarithm, so that the estimated responses can be interpreted as elasticities with respect to oil price changes. In columns 1-3, we look at the effect of oil price shocks on indicators for tax burden, corruption and unemployment. Tax burden is measured by (log) tax revenue as a percentage of GDP from World Development indicators (World Bank, 2018), corruption data is taken from ICRG (PRS, 2017) with higher values referring to lower corruption and (log) unemployment is calculated according to International Labor Organization (ILO) estimates and retrieved from World Development Indicators (World Bank, 2018).[16] The results show that negative oil price shocks leave no statistically significant impact on any of these variables.

Table 6: Oil price shocks and other potential mechanisms

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ logTax	**Δ log Corruption**	**Δ log Unempl**	**Δ logBusiness Freedom**	**Δ logCredit market regulations**	**Δ logNetSchool Enrollment (primary)**	**Political instbility**
	OLS	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**
3-year average oil price shock, *t*	-0.418 (0.943)	-0.040 (0.176)	-0.220 (0.147)	-0.091 (0.122)	0.215 (0.292)	-0.018 (0.089)	0.234 (0.631)
Number of observations	2,279	2,911	3,563	2,893	2,007	1,909	3402
Number of countries	134	131	156	156	150	145	149
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country specific-time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes

3-year average oil price shock is the average three year ln-change in the oil price multiplied by whole period average oil exports share to GDP (1991-2015). The method of estimation is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the country level. Country fixed effects and country-specific time trend are not reported. Significantly different from zero at *90% confidence, **95% confidence, ***99% confidence.

In columns 4 and 5, we look at effect on the efficiency of market regulations using two indicators. Business freedom indicator from Heritage Foundation (2018) measuring the extent to which the regulatory and infrastructure environments constrain the efficient operation of businesses. It ranges from zero to 100 with higher values referring to more regulations. The other indicator is credit market regulations from Fraser Institute (2018). It capture regulatory restraints that limit the freedom of exchange in credit markets and ranges from 0 to 10, with higher values referring to less regulations. The results in both cases reveal no effect of oil price shocks on the quality of market regulations. Column 6 indicates that educational attainment, as measured by net secondary school enrollment (World Bank, 2018), is not affected by oil price shocks. Finally, column 7 shows that negative oil price increase political instability, measured by regime durability index from Polity IV database (Marshall and Jaggers, 2018), but the result is statistically insignificant. The index measures the number of years since the most recent regime change that alters essential authority characteristics, as defined by a three-point change in Polity in a three-year period or less.

Taken together, our results show that oil price shocks can also affect shadow economy through increasing the likelihood of protest, an aspect that, if ignored, can potentially bias our estimates. Therefore, we account for this by adding *Protest count* as an additional control variable, when estimating the 2SLS estimates in equation (3). The idea is that if GDP per capita is the dominant mechanism, then we shall expect all other mechanisms to be statistically insignificant when confronted against it.[17] Results are presented in table 7 which reports the two-state least squares (2SLS) estimates for the effect of the effect of oil price shocks on the shadow economy assuming that the effect occurs through GDP. Column 1-3 estimates the effect on change of the (log) shadow economy. The 2SLS estimates in column 2 indicate that the negative income shocks have a positive and statistically significant effect on the size of the shadow economy, when instrumented by the 3-year average oil price shock at t. Specifically, a 1 percentage point decline in GDP per capita increases the shadow economy by 0.54 percentage points at

[16] Tax burden is also measured using Heritage Foundation's measure of fiscal burden, referring to average and marginal corporate and personal income taxation (Heritage Foundation, 2018). A higher score (on a scale of 0–100) implies more burdensome taxation. We find the effect to remain insignificant (results available upon request).

[17] This is the same approach followed by Dix-Carneiro, Soares and Ulyssea (2018).

1 percent significance level. It then follows that a 10 percentage point drop in oil prices leads to an increase in the size of the shadow economy by 0.54 × 0.54 = 0.29 percentage point for every 10 percentage point increase of the oil exports over GDP. In Column 3, we augment our specification by adding the number of protest as an additional control variable. The 2SLS estimates of the effect of GDP on the shadow economy remain quantitatively and qualitatively the same and the effect of protest enters statistically insignificant. For comparison, we report the least squares estimates in column 1, which have the same sign and statistical significance as the 2SLS estimates.

Table 7: Oil price shock, shadow economy and GDP per capita

Model	(1)	(2)	(3)	(4)	(5)	(6)
	Δ logSE	Δ logSE	Δ logSE	logBC-SE	logBC-SE	logBC-SE
	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Δ logGDP per capita, *t*	-0.500***	-0.536***	-0.536***	-0.548***	-0.975***	-0.982***
	(0.082)	(0.176)	(0.178)	(0.093)	(0.235)	(0.237)
Protest Count			-0.001			-0.002
			(0.002)			(0.002)
	First stage for Δ GDP per capita, *t*					
3-year average oil price, *t*		0.537***	0.534***		0.187***	0.107**
		(0.118)	(0.118)		(0.029)	(0.053)
First stage F-statistic		20.56	20.50		42.76	41.66
Kleibergen-Paap *(P value)*		0.01	0.01		0.00	0.00
Number of observations	3,469	3,469	3,469	3482	3482	3482
Number of countries	155	155	155	155	155	155
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Country specific-time trend	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable in columns 1, 2 and 3 is the ln-change in the size of the shadow economy as a percentage of GDP; in columns 4, 5 and 6 is the log business-cycle component of the log-shadow economy generated by HP filter. The logGDP per capita for columns 4, 5 and 6 is the log business-cycle component of the log-GDP per capita generated by HP filter. In top panel, we report estimates of the average impact of oil price shocks. The method of estimation in columns 1 and 4 is ordinary least squares; in columns 2, 3, 5 and 6 is two-stage least squares with Huber-robust standard errors (reported in parentheses) clustered at the country level. The instrumental variable is the 3-year average oil price shock defined as the average three year ln-change in the oil price multiplied by whole period average oil exports share to GDP (1991-2015). In the bottom panel, we report the corresponding first stage regressions with Huber robust standard errors (in parentheses) that are clustered at the country level. Country fixed effects and country-specific time trend are not reported. Significantly different from zero at *90% confidence, **95% confidence, ***99% confidence.

Columns 4-6 examine the effect of GDP-growth cycles driven by oil price shocks on the corresponding shadow economy's growth cycles. The 2SLS estimate in column 5 implies that a 1 percentage point decline in GDP per capita increases the shadow economy by 0.98 percentage point at 1 percent significance level. The ordinary least squares estimate and conditional 2SLS estimate in columns 4 and 6, respectively report as well a positive impact of negative income growth shocks on the shadow economy. To summarize, the results indicate that the shadow economy responds negatively to negative income shocks, or on other words behaves in a countercyclical fashion. Throughout the models, the negative statistical significant effect of oil-driven-GDP growth lends credence that income shocks are the dominant mechanism through which oil price shocks affect the size of the shadow economy.

V. Robustness Checks

The following robustness checks are performed one at a time: (i) drop major oil producers and OPEC countries, when estimating equation (3); (ii) exclude non-oil producing countries; (iii) differentiate the impact between developed and developing countries; (iv) Add dynamic effects; (vi) use different weight for oil price shocks; (vi) use alternative measures for the size of the shadow economy. Since the growth-cycles measure of the shadow economy growth continue to perform as simple year-to-year changes, we only report results using the latter measure to save space.

Table 8 presents our estimates for equation (3) after making a set of exclusions for a specific groups of countries. Because international oil prices can be endogenous, in the sense that major oil producing and exporting countries may affect world oil supply to increase or decrease market prices. Columns 1 and 2 examines the effects of oil price shocks on shadow economy after excluding OPEC countries and major oil producing countries. The latter group refers to the top 10 percent oil producers or countries producing (over the whole-period average) more than 1.6 percent of world oil production.[18] Major oil producing countries are identified using Ross and Mahadavi (2015) dataset on oil production covering the period 1932-2014 and based on World Bank's 'Wealth of Nations' database and EIA data on production volumes.[19] We find negative oil price shocks continue to exhibit a positive statistically significant impact on shadow economy. Although, the size of the effects becomes smaller compared to table 4. This may be related to the fact that most excluded countries are also the ones having the highest shares of shadow economies (10 out 17 excluded countries have a mean size of shadow economy of about 37 percent of GDP).

Table 8: Excluding country groups

Model	(1)	(2)	(3)	(4)
	Exlude OPEC	Exclude major oil producers	Exclude non-oil producers	Exclude low-oil producers (median)
	Δ logSE	Δ logSE	Δ logSE	Δ logSE
Δ GDP per capita, *t*	-0.396*	-0.263**	-0.539***	-0.537***
	(0.218)	(0.130)	(0.180)	(0.181)
	First stage for Δ GDP per capita, *t*			
3-year average oil price, *t*	0.634***	0.572***	0.529***	0.526***
	(0.169)	(0.152)	(0.119)	(0.119)
First stage F-statistic	14.02	14.23	19.79	19.52
Kleibergen-Paap *(P value)*	0.059	0.047	0.012	0.013
Number of observations	3,217	3,103	2,030	1,717
Number of countries	143	138	91	77
Country FE	Yes	Yes	Yes	Yes
Country-specific time trend	Yes	Yes	Yes	Yes

The dependent variable is the ln-change in the size of the shadow economy as a percentage of GDP. The method of estimation is two-stage least squares with Huber robust standard errors (in parentheses) that are clustered at the country level. The instrumental variable is the 3-year average oil price shock defined as the average three year ln-change in the oil price multiplied by whole period average oil exports share to GDP (1991-2015). In the bottom panel, we report the corresponding first stage regressions. Country fixed effects and country-specific time trend are not reported. Significantly different from zero at *90% confidence, **95% confidence, ***99% confidence.

In columns 3 and 4, we check our estimates by excluding non-oil and low oil producing countries. The idea is that having some countries with zero or near zero oil production can downward bias our estimates by inflating our sample with many observations than have no statistical significance effect. Hence, excluding those countries leaves us with a more homogenous sample and a better control group. Non-oil producing countries are countries having a zero oil production over the whole-period average and low-oil producing countries are the ones whose oil production levels are below the median score over the whole-period average. Results turn out to be very similar in magnitude and statistical significance to our baseline estimates. Our results still indicate a strong negative significant relationship at 1 percent significance level, even after losing around 47 percent of our baseline sampled observations.

Shadow economy causes and drivers can differ between developed and developing countries. In table 9, we split the sample into two subsamples of countries according to the World Bank's income classification. The developing countries is comprised of middle income (both upper middle-income and lower middle-

[18] We also checked results by excluding countries producing more than 3 percent and 10 percent of world oil production (results available upon request).

[19] Although the production figures from Ross and Mahadavi (2015) dataset stops at 2014 or one year before the end of the period of analysis, this should not be of major concern, since we are focusing the whole-period average (time-invariant) production levels. Thus, they are not much affected by the exclusion of one year.

income) and low-income countries, whereas the developed countries refer to the high-income category[20]. Column 1 shows the 2SLS estimates for the developed countries and column 2 contains the estimates for the developing countries. The downside of this sample split is that the resulting subsample for the developed countries group ends up having fewer observations, which may affect the quality of estimation. In particular, although the effect of oil-driven GDP growth in both subsamples share the negative same sign, the estimates in the sample of the developed countries suffer from underidentification (according to Kleibergen-Paap test of underidentification) and therefore the results should be taken with caution. For the developing countries, we find that a 1 percentage point decline in GDP growth following negative oil price shock significantly increases the size of the shadow economy by 0.35 percentage point at 1 percent significance level, which is lower than the reported effect in our full sample.[21]

Table 9: Developed and developing countries subsamples

Model	(1)	(2)
	Developed Countries	Developing Countries
	Δ logSE	Δ logSE
Δ logGDP per capita, *t*	-3.497	-0.348***
	(2.477)	(0.101)
A-R Wald, F *(P value)*	[0.063]*	
A-R Wald, χ^2 *(P value)*	[0.049]**	
Stock-Wright, LM *(P value)*	[0.090]*	
	First stage for Δ GDP per capita, *t*	
3-year average oil price, *t*	0.102	0.736***
	(0.083)	(0.146)
First stage F-statistic	1.51	25.59
Kleibergen-Paap *(P value)*	0.256	0.016
Number of observations	1,095	2,374
Number of countries	49	106
Country FE	Yes	Yes
Country-specific time trend	Yes	Yes

The dependent variable is the ln-change in the size of the shadow economy as a percentage of GDP. In column 1, we report estimates for developed countries and in column 2 for developing countries. Based on the World Bank income classification, developed countries are all countries belonging to high income countries categories, while developing countries are low income, low-middle and upper-middle income countries. The method of estimation is two-stage least squares with Huber robust standard errors (in parentheses) that are clustered at the country level and p-values [in square brackets] for three significance tests that are robust to weak instruments and the versions we implement are robust to heteroscedasticity and arbitrary within-country correlation of the residuals. The instrumental variable is the 3-year average oil price shock defined as the average three year ln-change in the oil price multiplied by whole period average oil exports share to GDP (1991-2015). In the bottom panel, we report the corresponding first stage regressions. Country fixed effects and country-specific time trends are not reported. Significantly different from zero at *90% confidence, **95% confidence, ***99% confidence.

Table 10 adjusts our baseline estimations in tables 4 and 6 by including the lagged dependent variable as an additional explanatory variable. This shall create a correlation between the lagged dependent variables and error introducing what is often referred to as the Nickel bias (Nickel, 1981). Hence, besides reporting OLS and 2SLS estimates, we also report the system-generalized method of moment (GMM) (Blundell and Bond, 1998). The estimates in table 10 are very similar to our baseline results and the results from system-GMM estimation are very close to the original least squares results.[22] The results in column 1 indicate that the shadow economy adjusts very slowly to shocks and that the long run effect is 3 times larger than the immediate effect. The long-run impact of oil price shock on the shadow economy implies

[20] The developed countries are Andorra, Antigua and Barbuda, Argentina, Aruba, Australia, Austria, Bahamas, Bahrain, Barbados, Belgium, Brunei, Canada, Chile, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea Rep., Kuwait, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Monaco, Netherlands, New Caledonia, New Zealand, Norway, Oman, Panama, Poland, Portugal, Qatar, Saudi Arabia, Seychelles, Singapore, Slovakia, Slovenia, Spain, St. Kitts and Nevis, Sweden, Switzerland, Switzerland, Taiwan, Trinidad and Tobago, United Arab Emirates, United Kingdom, United States, Uruguay.

[21] Although, checking the results with growth cycles measure of shadow economy growth, found that the effect is negative and statistically significant in both subsamples.

[22] The Time dimension of our sample of T=25 generally reduces concerns with Nickel bias (see Nickel, 1981) in OLS specification. According to Beck and Katz (2011), Nickel Bias becomes smaller when T is 20 years or more. It is therefore not surprising to see that the results from system-GMM estimation are very close to the original least squares results. We also use the collapse option to reduce the instruments count.

that a 10 percentage point decline in oil prices increases the shadow economy by 0.84 percentage point for each 10 percentage point increase of oil exports over GDP. In column 3, the long-run effect of oil-price-driven GDP growth on shadow economy is around 4 times the immediate impact and implies that a 1 percentage point decline in GDP increase the shadow economy by 2.3 percentage point.[23]

Table 10: Add dynamic effects

Model	(1)	(2)	(3)	(4)
	Δ logSE	Δ logSE	Δ logSE	Δ logSE
	OLS	Sys-GMM	2SLS	Sys-GMM
3-year average oil price shock, *t*	-0.299***	-0.395***		
	(0.092)	(0.102)		
Δ logGDP per capita, *t*			-0.603***	-0.665***
			(0.167)	(0.097)
Lagged logSE (level)	-0.354***	-0.359***	-0.258***	-0.290***
	(0.021)	(0.038)	(0.031)	(0.035)
AR(1)		0.000		0.000
AR(2)		0.839		0.251
AR(3)		0.627		0.730
Excluded Instruments				3-year average oil price, t
	First stage for Δ GDP per capita, *t*			
3-year average oil price shock, *t*			0.557***	
			(0.129)	
First stage F-statistic			18.78	
Kleibergen-Paap *(P value)*			0.012	
Number of observations	3,563	3,563	3,469	3,469
Number of countries	156	156	155	155
Country FE	Yes	Yes	Yes	Yes
Country-specific time trend	Yes	Yes	Yes	Yes

The dependent variable is the ln-change in the size of the shadow economy as a percentage of GDP. The method of estimation in column 1 is ordinary least squares with Huber-robust standard errors (reported in parentheses) clustered at the country level; columns 2 and 4 is system-GMM; column 3 is two-stage least squares. The instrumental variable is the 3-year average oil price shock defined as the average three year ln-change in the oil price multiplied by whole period average oil exports share to GDP (1991-2015). In the bottom panel, we report the corresponding first stage regressions. Country fixed effects and country-specific time trend are not reported. Significantly different from zero at *90% confidence, **95% confidence, ***99% confidence.

In constructing our indicator for oil price shocks, we weigh the ln-change in oil prices with the average of oil exports over GDP for the period 1991-2015. If the country's share of oil exports to GDP is stable over time or at least does not show large fluctuations, then it will not matter taking the average of oil exports over GDP for our sample period or extending it to include years before our starting period. To check that, columns 1 and 2 in table 11 report estimates the OLS and 2SLS of the effect of oil price shocks on the shadow economy after recalculating the average value of oil exports over GDP over the period 1973-2015.[24] The effects continue to remain negative and statistically significant, despite being slightly quantitatively larger. In columns 3 and 4, we recalculate the value of oil exports over GDP to correspond to 1990, or before the beginning of our sample period to count out any effect of oil price fluctuations post 1990 on our measure of oil exports. The main result is that negative oil price shocks and oil-price driven negative GDP growth continue to have a significantly positive effect on the shadow economy.

[23] The long run impact is calculated by multiplying the estimated coefficient with inverse of the lagged dependent variable coefficient times -1.

[24] We start from year 1973, which marks the year in which oil became a strategic good following the oil crisis in 1973. We also checked by taking the share of oil exports to GDP at mid-point in year 2003 and the results remain robust (results available upon request).

Table 11: Changing export shares and impact in non-oil producing countries

Model	(1)	(2)	(3)	(4)
	Export shares 1973-2015	Export shares 1973-2015	Export shares 1990	Export shares 1990
	Δ logSE	Δ logSE	Δ logSE	Δ logSE
	OLS	2SLS	OLS	2SLS
3-year average oil price shock, *t*	-0.313***		-0.395***	
	(0.074)		(0.079)	
Δ logGDP per capita, *t*		-0.649***		-1.048***
		(0.190)		(0.312)
	First stage for Δ GDP per capita, *t*			
3-year average oil price, *t*		0.514***		0.416***
		(0.136)		(0.135)
First stage F-statistic		14.37		10
Kleibergen-Paap *(P value)*		0.004		0.008
Number of observations	3,563	3,469	3,036	2,959
Number of countries	156	155	132	131
Country FE	Yes	Yes	Yes	Yes
Country-specific time trend	Yes	Yes	Yes	Yes

The dependent variable is the ln-change in the size of the shadow economy as a percentage of GDP. The method of estimation in columns 1 and 3 is ordinary least squares; in columns 2 and 4 is two-stage least squares with Huber-robust standard errors (reported in parentheses) clustered at the country level. The instrumental variable in column 2 is the 3-year average oil price shock defined as the average three year ln-change in the oil price multiplied by whole period average oil exports share to GDP (1973-2015); in column 4 is the 3-year average oil price shock defined as the average three year ln-change in the oil price multiplied by oil exports share to GDP in 1990. In the bottom panel, we report the corresponding first stage regressions. Country fixed effects and country-specific time trends are not reported. Significantly different from zero at *90% confidence, **95% confidence, ***99% confidence.

Finally, in table 12, we check whether our estimates are sensitive to the specific measure of the shadow economy. We employ two alternative measures for shadow economy. The first is based on Elgin and Oztunali's (2012) estimates, who use a dynamic general equilibrium approach to measure the size of the shadow economy in 161 countries over the period 1950-2009. The second comes from Alm and Embaye (2013) with estimates based on the currency demand method for the period 1984-2006. In our sample, the correlation between Medina and Schneider's (2017) estimates of the shadow economy with Elgin and Oztunali's (2012) is 0.97 and with Alm and Embaye (2013) is 0.78. Columns 1 and 2 shows the OLS and 2SLS estimates using Elgin and Oztunali's (2012) dataset, and columns 3-4 reports the effects using Alm and Embaye (2013) dataset. Given that the first stage F-statistic in column 4 is below 10, the recommended threshold by Staiger and Stock (1997), we therefore use weak-instrument robust inference p values (reported in square brackets) to assess significance. Throughout the models, shadow economy continues to significantly respond positively to negative oil price shocks and negative oil-price-driven GDP growth. Although the estimates in column 4 are statistically insignificant based on the traditional cut-off points of significance (1, 5 and 10 percent), they nevertheless tend to significance based on based on the Anderson-Rubin test of statistical significance in brackets (A-R Wald).[25]

In the online appendix, we conduct additional robustness checks. In table A3, we differentiate between negative and positive oil price shocks by including in equations (2) an interaction term between oil price shocks and indicator that equals 1 if the annual ln-change in oil prices is strictly negative. The interaction term enters insignificant and the linear affect remains negative and statistically significant. In table A4, we check whether the counter-cyclicality of the shadow economy depends on its initial size. For this, we include in equation (3) an interaction term between GDP and the lagged level of the shadow economy.

[25] We also checked the results using the dataset from Schneider, Buehn, and Montenegro (SBM) (2010) with estimates based on the MIMIC approach for the period 1999-2007. Despite obtaining the same results, the estimates are not robust to the inclusion of country-specific time trends and country-clustered standard errors.

Again, the interaction term has statistically insignificant effect and the GDP continues to exhibit a significant negative impact on the shadow economy. In table A5, we look at the effect of oil price shocks (oil-price-driven GDP growth) in non-oil producing countries by including an interaction term between oil price shocks (GDP growth) and a dummy variable that takes the value of 1, if a country's average production of oil is zero over the whole period sample. The interaction term is shown to be statistically insignificant, whereas the linear effect remains negative and statistically significant, meaning there is no difference in effect between oil producing and non-producing countries. In table A6, we perform a falsification test to make sure that the observed effects is not simply data-driven by regressing the oil price shocks (GDP growth) on randomly generated fake observations for the shadow economy. We find that oil price shocks (GDP growth) have no statistical significant effect on shadow economy. In table A7, we look at the average impact of oil-price-driven GDP growth on the shadow economy during periods of low international oil prices (i.e. bust periods). We define those periods as all years in which oil prices are strictly lower than their long-run average calculated as a simple average of oil prices over the period 1973-2015.[26] Bust is then a dummy variable that equals 1 for the years 1991-2004, and zero otherwise.[27] We interact the bust dummy with GDP growth and find that the interaction term is statistically insignificant, while the linear effect remain statistically negative significant. Therefore, there is no evidence that the impact of GDP is significantly different between bust and boom periods.

Table 12: Using different estimates for the shadow economy

Model	(1)	(2)	(3)	(4)
	Elgin and Oztunali	Elgin and Oztunali	Alma and Embage	Alma and Embage
	Δ logSE	Δ logSE	Δ logSE	Δ logSE
	OLS	2SLS	OLS	2SLS
3-year average oil price shock, *t*	-0.052**		-0.776*	
	(0.024)		(0.452)	
Δ logGDP per capita, *t*		-0.180*		-1.737
		(0.094)		(1.115)
A-R Wald, F *(P value)*				[0.124]
A-R Wald, χ^2 *(P value)*				[0.109]
Stock-Wright, LM *(P value)*				[0.182]
		First stage for Δ GDP per capita, *t*		
3-year average oil price, *t*		0.324***		0.399***
		(0.073)		(0.153)
First stage F-statistic		19.72		6.79
Kleibergen-Paap *(P value)*		0.019		0.022
Number of observations	4,865	4,521	2,066	2,034
Number of countries	158	157	111	110
Country FE	Yes	Yes	Yes	Yes
Country-specific time trend	Yes	Yes	Yes	Yes

The dependent variable is the ln-change in the size of the shadow economy as a percentage of GDP. The method of estimation in columns 1 and 3 is ordinary least squares; in columns 2 and 4 is two-stage least squares with Huber-robust standard errors (reported in parentheses) clustered at the country level. The instrumental variable is the 3-year average oil price shock defined as the average three year ln-change in the oil price multiplied by whole period average oil exports share to GDP (1991-2015). In the bottom panel, we report the corresponding first stage regressions. Country fixed effects and country-specific time trends are not reported. Significantly different from zero at *90% confidence, **95% confidence, ***99% confidence.

VI. Conclusion

In this paper, we study the impact of oil price shocks on the incidence of protest over the period 1991-2015. Our results indicate that negative oil price shocks lead to an increase in the number of protests and

[26] We start from year 1973 when calculating the long average of oil prices, despite the fact that our period of analysis starts in 1991, to better capture those low/high price periods that could have occurred even before 1991, and especially after oil became a strategic good following the oil crisis in 1973.

[27] We decided not to include year 2015 in the bust period in order to avoid the distortion that might be introduced by observations that belong a very short high volatility period of price fluctuations rather than a lasting price decline period.

that a higher initial size of the shadow economy allows to mitigate the negative consequences of low oil prices on the likelihood of protest. In explaining this result, this paper contributes to the existing debate in the shadow economy literature of whether the shadow economy behaves pro-cyclically or counter-cyclically to economic shocks. We provide new evidence that the shadow economy is negatively associated with oil price shocks. In highly oil dependent countries, a 10 percentage point drop in international oil prices increases the shadow economy on impact by 0.26 percentage point for each 10 percentage point increase in oil exports over GDP. We find this countercyclical behavior is largely explained by oil-price-driven income shocks. A 1 percentage point increase in the GDP per capita increases the shadow economy by 0.54 percentage point. Therefore, unlike previous studies regarding the shadow economy as a burden, our results suggest that counter-cyclicality of the shadow economy may act as a shock absorber, providing an insurance mechanism for business and labor against economic downturns. A higher size of the shadow economy can thus contribute to the political stability by providing a complementary source of income in highly resource dependent countries with economies relatively vulnerable to external economic shocks.

This fact has several implications. First, such mitigating role should allow for reconsiderations of permanent calls to eliminate the unofficial economy, by depicting it as a source of all evil, a stance that simply conflates causes with symptoms. Governments have to recognize that the existence of a shadow economy serves implicitly or explicitly as an integral part of societies' social risk management strategies (Holzmann and Jørgensen, 2001). Second, even if the elimination of inefficiencies in the allocation of goods and factors in the economy is an aim, which is justified in its own, deregulation and structural adjustment strategies have to be designed carefully. Specifically, strategies have to be implemented in such a way, that a reduction or abolishment of certain risk management pillars will be complemented by the increase or establishment of other pillars (social security payments, unemployment insurance,…etc.). Third, diversification of production will reduce the dependence from e.g. oil production. Therefore industrial diversification strategies can serve as an important complement to strategies aiming at reducing the role of the shadow economy. In the end, the existence of the shadow economy is always also a response to unsound economic policies and inefficient economic structures that fail to shield the economy against shocks, aspects that should be addressed in advance before resorting to easy solutions.

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