A Resource-Rich Neighbor Is a Misfortune: The Spatial Distribution of the Resource Curse in Brazil

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I. Introduction

The existence of the natural resource curse as a firmly established stylized fact has been tarnished by findings that emphasize the benefits for areas where those resources are extracted (Black, McKinnish, and Sanders 2005; Alexeev and Conrad 2009; Aragón and Rud 2013; Cotet and Tsui 2013; Allcot and Keniston 2018; Bartik et al. 2019; Mamo, Bhattacharyya, and Moradi 2019; Gradstein and Klemp 2020; Bhattacharyya and Mamo 2021). Do those results mean, however, that natural resources are a curse for no one? In this paper we argue the contrary. The spatial dimension of the effect of natural resources is all-important because the benefits and costs of resource windfalls are unevenly distributed across space.

Specifically, municipalities that produce oil probably benefit from the activity and revenues that natural resources generate, and their economies therefore grow. But as they grow, these municipalities draw on resources from other neighboring municipalities, thereby imposing negative spillovers. Municipalities that produce oil may also impose costs through increases in crime, corruption, or conflict. Hence, the balance between the benefits and costs of natural resources is likely spatially uneven, with positive effects dominating in the

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vicinity of resource-producing municipalities and fading with distance. As a result, some non-resource-producing municipalities may suffer from resource windfalls.

Moreover, the net aggregate effect may be either insignificant or negative despite the positive direct effect. Consequently, the effect of natural resources measured at the local level may be positive, but it may prove insignificant or even negative when observed at higher levels of aggregation, such as in regions or countries. That may explain why subnational studies report unmitigated positive effects, while the findings of cross-country studies are contradictory (Sachs and Warner 1995, 2001; Auty 2001; Alexeev and Conrad 2009; Cotet and Tsui 2013).

We test this hypothesis using data on oil and gas revenues in Brazilian municipalities. Brazil is an appealing case for several reasons. First, it is the world's tenth-largest oil producer, but it is not a member of the Organization of Petroleum Exporting Countries. This implies that while oil production is important to Brazil's economic health, its influence on world prices is limited. Furthermore, there is an official distinction between oil-producing and non-oil-producing municipalities.[1] Brazil has designed a system whereby oil and gas revenues automatically accrue to oil-producing municipalities and states in the form of royalties. As a result, municipalities are the natural units of observation to gauge the effect of oil on performance.[2] Moreover, as the system allocates the revenues of oil wells, it implies that fluctuations in the oil price automatically affect the oil revenues of those municipalities. Finally, the specific features of Brazilian production allow us to identify the causal impact of oil and gas revenues on the country's municipalities. We do so by exploiting the fact that oil and gas price fluctuations are exogenous to whatever happens in each municipality. We can therefore compute an exogenous component of oil and gas revenues by multiplying the initial level of production of each municipality by the prices of those resources. Since these prices are determined on global markets, the result of that product can safely be considered exogenous to Brazilian municipalities.

To study the geographic dimension and the spillover effects of oil, we follow Mamo, Bhattacharyya, and Moradi (2019) and chiefly estimate a spatial Durbin model (SDM), which relates the performance of a municipality to its own oil revenues and to those of adjacent municipalities.[3] Hence, it allows us to determine the sign and magnitude of the effects of oil revenues on both

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[1] In Brazil, gas production is a by-product of oil production. To be concise, we refer to oil production or oil-producing municipalities only, even though they may produce both oil and gas.

[2] See app. C (apps. A–C are available online) and Caselli and Michaels (2013) for an overview of oil production and oil-producing municipalities in Brazil.

[3] See also Harari and La Ferrara (2018) for a similar procedure.

oil-producing and non-oil-producing municipalities. To supplement this analysis, we also model spillovers using distance to the nearest oil-producing municipality to study more precisely how spillovers vary as one moves away from oil-producing municipalities. We also look at wider units of observation, specifically micro- and macroadministrative units. By construction, these units include both oil-producing and non-oil-producing municipalities. By studying the effect of oil on those aggregated units, we can, de facto, observe the sum of the direct effect of oil and its spillovers.

Our workhorse measure of economic performance is nighttime light emissions, which have been used as a proxy for gross domestic product (GDP) at the subnational level (e.g., Henderson, Storeygard, and Weil 2012; Hodler and Raschky 2014; Villa 2016; Dickens 2018; Mamo, Bhattacharyya, and Moradi 2019; Amarasinghe et al. 2020). Data on these emissions have a number of advantages over official municipal GDP figures, making them particularly suitable for analyzing the spatial distribution of the effect of natural resources on activity in Brazil. First, emissions data cover a longer period of time, as the official municipal GDP figures are available on an annual basis from 1999 onward only. Second, in contrast to official GDP figures, nighttime light emissions data capture any type of economic activity, both official and nonofficial, especially at the subnational level where official statistics are otherwise lacking or unavailable. This is particularly important in Brazil, where at least 40% of the working population are informal workers (Henley, Arabsheibani, and Carneiro 2009). Third, and most important, municipal GDP is not computed directly by the Brazilian national bureau of statistics (Instituto Brasileiro de Geografia e Estatística [IBGE]; https://www.ibge.gov.br/en/home-eng.html). Instead, it is inferred from state GDP, divided among municipalities according to a number of reference variables. For oil-producing municipalities, the reference variable used to assign municipal industry GDP is the same as the one used for assigning oil production to municipalities, thus creating a tautological correlation between oil production and official GDP. By using nighttime light emissions, we can study a relationship that is not a spurious artifact of the way Brazilian authorities impute state GDP to municipalities. To investigate the transmission channel of the direct and spillover effects of oil and gas revenues, we also replace that baseline dependent variable with a series of variables measured at the municipality level.

Our paper contributes to the broad literature on the natural resource curse, pioneered by Sachs and Warner (1995, 2001) or Auty (2001), who reported that growth was lower in resource-rich countries. More specifically, our paper contributes to the literature that investigates the effect of natural resources on economic performance and development at the subnational level (e.g., Black, McKinnish, and Sanders 2005; Michaels 2011; Caselli and Michaels 2013; Allcot and Keniston 2018; Gradstein and Klemp 2020; Noack 2020). It also contributes to work on the spatial spillovers of natural resources, whether on economic performance (Aragón and Rud 2013; Mamo, Bhattacharyya, and Moradi 2019) or gender relations (Kotsadam and Tolonen 2016). In particular, our research supplements papers by Caselli and Michaels (2013); Mamo, Bhattacharyya, and Moradi (2019); and Gradstein and Klemp (2020). Like us, Caselli and Michaels (2013) and Gradstein and Klemp (2020) study the effects of oil revenues in Brazil. Unlike Caselli and Michaels (2013), we look at the effect of those revenues on economic activity, as opposed to public spending. Moreover, we do this at the level of municipalities, whereas Caselli and Michaels's (2013) units of observation are *áreas mínimas comparáveis* ("minimum comparable areas"), a statistical geographic unit that is typically larger than municipalities. We share our focus on oil in Brazil with Gradstein and Klemp (2020) but depart from their analysis with our main focus on the spatial spillovers of oil and gas revenues between municipalities.

We use several techniques designed to capture these spillovers and study how they change across space. In particular, we allow spillovers to interact in a nonlinear way with geographic distance. We also consider the revenues of both oil and gas, as opposed to oil only. Although gas is in essence a by-product of oil production, and Brazil's gas production barely covered its consumption over most of our study period, it still contributed to the revenue windfall from hydrocarbon production. Our explanatory variable is the product of current oil and gas prices and initial oil and gas production, which is in line with the rule used to share oil and gas revenues among Brazilian municipalities. By contrast, Gradstein and Klemp (2020) considered the product of oil price and distance to the nearest oil field. For that reason, our explanatory variable better approximates a municipality's oil and gas revenues, which are a function of both prices and quantities. And by focusing on municipalities within oil-producing states rather than also including those in non-oil-producing states, we can work with a more homogenous sample and capture the redistributive effects of oil and gas revenues within states. Mamo, Bhattacharyya, and Moradi (2019) study the production of 21 minerals in 42 sub-Saharan countries at the level of districts. By focusing on oil production only, and specifically on oil-producing states within a country, we consider observations that are institutionally homogeneous and take advantage of the specific features of oil revenue distribution among Brazilian municipalities. In addition, with variations in prices being plausibly exogenous, we can better assess the causal impact of revenue windfall. Finally, as the bulk of Brazilian oil production is exogenous, the risk of overglowing because of gas flaring on extraction sites is limited in our case.

We confirm that oil and gas revenues have a positive direct effect on economic activity in oil-producing municipalities. That finding is obtained even using light emissions, in contrast to Gradstein and Klemp's (2020) results. Our estimates suggest that a 10% increase in revenues boosts economic activity by an average of 1.4% in oil-producing municipalities. By contrast, non-oil-producing municipalities are shown to suffer negative spillovers from oil and gas revenues, with the effect nearly equal in magnitude to that of the direct impact. Furthermore, by employing distance-weighted measures of oil and gas revenues, we find that negative spillovers strengthen, relative to direct effects, as the distances between a municipality and oil-producing locations increase. According to our estimates, significant negative spillovers start to dominate in municipalities located around 150 kilometers from oil activities, in contrast to Gradstein and Klemp (2020), who do not observe such spillovers. We document that oil and gas revenues affect royalties both in oil-producing municipalities and in neighboring municipalities. These revenues also increase population, real wages (particularly in manufacturing and service sectors), local prices, and crime. Moreover, we observe a negative spillover effect of oil and gas revenues on wages and prices and a positive spillover effect on crime in neighboring municipalities.

II. Spatial Distribution of the Effect of Oil and Gas Revenues: A Framework

A. Effect on Oil-Producing Municipalities

The effect of an increase in oil and gas revenues may be gauged using the theoretical frameworks provided by Moretti (2010), who investigated the arrival of a new producer in a municipality, and Allcott and Keniston (2018), who discussed natural resource booms. On the positive side, an increase in oil and gas revenues allows workers in the sector to increase their demand for intermediate goods, some of which may be locally produced, at least partially. Moreover, the revenues of oil-producing municipalities should rise, allowing them to increase their expenditures and resulting in increased demand for goods and services. For that reason, the direct effect of higher oil and gas revenues on local production is likely positive. Moretti (2010) and Allcott and Keniston (2018) moreover stress that the positive effect may be magnified in the presence of agglomeration economies, which can attract additional firms to oil-producing municipalities.

However, the frameworks of Moretti (2010) and Allcott and Keniston (2018) also imply that general equilibrium effects may mitigate direct and agglomeration effects. First, increased demand for labor increases wages and hence the cost of that labor. Whereas rising wages allow the booming oil sector to attract workers and increase production, higher labor costs reduce the production of other sectors. That effect may be particularly harmful to producers of goods that are traded with other municipalities, because those producers are unable to increase their prices. As a result, the production of tradeable goods may move from oil-producing municipalities to other municipalities. Second, prices of goods and services and of housing in oil-producing municipalities may rise because of higher labor costs, further increasing production costs for local producers and driving them away.

The relative magnitude of direct and general equilibrium effects is ambiguous. Accordingly, the effect of an increase in oil and gas revenues is, in principle, ambiguous. Whether it increases or decreases local production is therefore an empirical question.

B. Spatial Spillovers of Oil and Gas Revenues

At first glance, it may seem doubtful that oil and gas revenues have any effect whatsoever on non-oil-producing municipalities, if natural resource extraction comes in the guise of "enclaves" with high productivity but limited spillovers, as McMillan, Rodrik, and Verduzco-Gallo (2014) documented. Yet whereas neighboring municipalities may not benefit from the direct effect of increased oil and gas revenues, they may be affected indirectly, with the indirect effects of oil and gas revenues potentially spreading geographically.

On the positive side, neighboring municipalities may benefit from stronger demand for intermediate goods from oil-producing municipalities. How far those effects spread depends on the length of the oil producers' supply chain. Unless transportation costs are negligible, those supply chain effects are likely smaller the farther a municipality is from the oil-producing municipality. Moreover, neighboring municipalities may benefit as the production of tradeable goods is driven away from oil-producing municipalities by rising wages.

Another positive effect is specific to the way that oil revenues are shared among Brazilian municipalities. Although the bulk of royalties accrues to oil-producing municipalities, neighboring municipalities are entitled to a small share if their land has been used for postproduction oil operations (i.e., storage and transportation).[4] Accordingly, neighboring municipalities may also benefit

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[4] This system of royalties was established in two sets of laws and decrees in 1989 and 1997. Oil producers automatically pay up to 10% of the value of their production as royalties to the federal state, which redistributes around 60% of those royalties, predominantly to oil-producing municipalities (Gradstein and Klemp 2020). The royalties that a municipality receives are proportional to the value of its production. We describe the mechanism in more detail in app. C. See also the descriptions provided by Monteiro and Ferraz (2010), Caselli and Michaels (2013), and Gradstein and Klemp (2020).

from a small increase in public expenditures, leading to higher demand for goods and services.

Conversely, neighboring municipalities may suffer from general equilibrium effects. In particular, the rise in the demand for labor in oil-producing municipalities is likely to spill over to neighboring municipalities if workers are sufficiently mobile across municipalities, also resulting in an increase in prices. In addition, workers may migrate to oil-producing municipalities to meet increased demand for labor in the oil sector.

Another source of negative spillovers would materialize if the increase in demand for goods and services in oil-producing municipalities also attracts scarce resources, such as capital and skilled labor. That could worsen bottlenecks in non-oil-producing municipalities and further decrease production; it could even reduce demand for unskilled labor, resulting in lower wages.

Again, increased oil revenues can generate positive or negative spillovers on neighboring municipalities, with the total effect being ambiguous. Despite this ambiguity, it stands to reason that whatever spillovers there are will decrease with distance to oil production, as transport costs will dampen the effect of oil revenues on the relocation of tradeable goods and worker migration. We should therefore expect those effects to be strongest in the immediate vicinity of oil-producing municipalities.

III. Empirical Strategy and Data

A. Empirical Strategy

To gauge the direct and spillover effects of oil and gas revenues on Brazilian municipalities, we estimate the following SDM:

$$\begin{aligned} y_{ist} = {} & \rho W Y_{ist} + \alpha_1 \log(\text{Revenues}_{ist}) + \alpha_2 W \Lambda(\text{Revenues}_{ist}) \\ & + \beta X_{ist} + \gamma W X_{ist} + \delta_i + \eta_t + \varepsilon_{ist}, \end{aligned} \tag{1}$$

where y_{ist} is the relevant measure of economic activity of municipality i in state s and year t, Y_{ist} is the vector containing the measure of economic activity of all of the other municipalities at the same time, δ_i represents municipality fixed effects, η_t represents year fixed effects, X_{ist} is a vector of time-varying controls, and ε_{jst} is the error term. Municipality fixed effects control for the differences across municipalities that are constant over time, while year fixed effects control for changes in the variables that affect all municipalities in the same year.

The main explanatory variable is the logarithm of oil and gas revenues, $\log(\text{Revenues}_{ist})$, computed as $\text{Oil}_{is,1992} \times P_t^{\text{oil}} + \text{Gas}_{is,1992} \times P_t^{\text{gas}}$, where $\text{Oil}_{is,1992}$ and $\text{Gas}_{is,1992}$ are the oil and gas production levels in municipality i and state s in 1992 and P_t^{oil} and P_t^{gas} are the international prices of oil and gas in year t.

As many municipalities produce no oil or gas, we add 1 to their revenues to avoid losing those observations when taking the logarithm of their revenue.[5]

The spatial dimension of economic activity and spillovers of oil revenues are captured by the contiguity spatial weight matrix W, which defines potential interactions between each pair of municipalities. Two municipalities are considered neighbors if they share a common border. A contiguous municipality is assigned a weight of $1/n_i$, where n_i is the number of municipalities contiguous to municipality i, and a nonneighboring municipality is assigned a weight of zero. Accordingly, WY_{ist} is the average economic activity in the municipalities that are adjacent to municipality i in state s at time t, and parameter ρ reflects the strength of spatial dependence in economic activities. By the same token, $W\Lambda(\text{Revenues}_{ist})$ denotes the product of matrix W with the vector containing the logarithms of oil and gas revenues in other municipalities. It therefore amounts to the average logarithm of revenues of municipality i's neighbors.

The first parameter of interest is α_1. It captures the direct effect of the oil and gas revenues of a municipality on the economic activity of that municipality. The second parameter of interest is α_2, which measures the specific effect on a municipality of the average oil and gas revenues in the neighboring municipalities. If oil and gas revenues in a municipality affected neighboring municipalities only because they affect economic activity in the oil-producing municipality, then their effect would be entirely captured by the spatial lag of the dependent variables, ρWY_{ist}. However, if oil revenues impose a specific spillover, then the spillover effect of oil and gas revenues will differ from the spillover effect of economic activity. Parameter α_2 captures that gap. Consequently, if $\alpha_2 < 0$, then spillovers from oil and gas revenues are smaller than the average spillover of economic activity. In that case, oil revenues in a municipality are detrimental to the economic activity of its neighbors. The opposite is true if $\alpha_2 > 0$.[6]

When assessing the effect of oil and gas revenues, a difficulty arises because the spatial weight matrix W implies that economic activity in a municipality is affected not only by the production and oil activity of its direct neighbors but also by all other municipalities in the sample, since their neighbors have neighbors and so on. As a result, the magnitudes of α_1 and α_2 cannot be interpreted directly, except in the special case where $\rho = \alpha_2 = 0$, which corresponds to the case where there is simply no spillover or feedback. We therefore compute and separately report the average effect of oil and gas revenues on economic

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[5] In app. B3, we show that the results are robust to dealing in a different way with municipalities with no oil and gas revenues.

[6] Note that if $\rho = \alpha_2 = \gamma = 0$, then the model is reduced to a standard linear regression model.

activities within oil-producing municipalities (direct effect), the average spillover effect on neighboring municipalities (indirect effect), and the average total effect (direct effect + indirect effect).[7] The average direct effect takes into account the feedback from neighboring municipalities in response to oil and gas revenues in municipality *i*. The feedback comes from the fact that if oil and gas revenues in municipality *i* affect its neighbors' economic activity, then municipality *i*'s activity will in turn be impacted by its neighbors' activity. The average indirect effect measures the average spillover imposed by oil-producing municipalities on their neighbors. The total average effect can be interpreted as the average total impact of oil and gas revenues on economic activities in a typical municipality if all municipalities had oil activities (LeSage and Pace 2014).[8]

To the extent that oil and gas prices are determined on the world market and that Brazilian municipalities are price takers, prices are exogenous to the local factors in those municipalities. Exogeneity is further ensured by setting the level of oil production at its level at the beginning of the sample period. Doing so overcomes endogeneity problems that would appear if oil discovery efforts and extraction rates are correlated with economic activity or an omitted variable that would affect them both, such as the quality of institutions (Cust and Harding 2020). In consequence, the variation in the value of oil production given by the product of the price of oil and the initial production level is plausibly exogeneous, and estimates of α_1 and α_2 should be unbiased and reflect causal effects.[9]

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[7] Once the spatial weight matrix W has been defined on the assumption that neighbors are municipalities that are contiguous, eq. (1) becomes a panel model that can be estimated by maximum likelihood. Parent and LeSage (2012) and Harari and La Ferrara (2018) provide a detailed derivation of the procedure. Lee and Yu (2016) show that the parameters of the model are then generally identified. Once α_1 and α_2 have been estimated, the average direct and indirect effects can be inferred. Specifically, the average direct effect is calculated as $[(I - \rho W)^{-1} \times (\alpha_1 I + \alpha_2 W)]^{\bar{d}}$, and the average indirect effect is calculated as $[(I - \rho W)^{-1} \times (\alpha_1 I + \alpha_2 W)]^{\overline{rsum}}$, where I is the identity matrix, the superscript $\bar{d}$ is the operator that calculates the mean diagonal elements of a matrix, and the superscript $\overline{rsum}$ is the operator that calculates the mean row sum of the nondiagonal elements of a matrix. They are computed using Stata's xsmle command written by Belotti, Hughes, and Piano Mortari (2013).

[8] Another interpretation could be that the total average effect measures the total cumulative impact arising from oil activities in municipality *i* on the economic activity of all other municipalities, on average (LeSage and Pace 2009).

[9] Similar procedures were used by Dube and Vargas (2013) and Nunn and Qian (2014). Moreover, the coefficient of correlation between the oil price and the annual variation of oil production at the national level is as low as -0.028. Accordingly, variations in the price of oil essentially result in an income windfall. We also tried setting production levels at midperiod, specifically at the average production level of 2002 and 2003, and results remain robust (see table B1; tables A1, B1–B4 are available online).

The SDM is estimated with maximum likelihood following Parent and LeSage (2012) and Yu, de Jong, and Lee (2008) and, by construction, addresses the endogeneity of WY.[10] We use robust standard errors and cluster them at the level of municipalities because the conventional way of clustering them when estimating SDMs is to do so at the level of units of observation, which in our case are municipalities (see Yu, de Jong, and Lee 2008; Parent and LeSage 2012).[11]

B. Data

Our baseline dependent variable, economic activity, is measured using the nighttime light emissions reported by the National Geophysical Data Center of the US National Oceanic and Atmospheric Administration (NOAA 2014). We use the Defense Meteorological Satellite Program Operational Linescan System data set that provides satellite-year data for the time period 1992–2013 and has been used as a proxy for GDP in recent studies (e.g., Doll, Muller, and Morley 2006; Henderson, Storeygard, and Weil 2012; Hodler and Raschky 2014; Michalopoulos and Papaioannou 2014; Keola, Andersson, and Hall 2015; Amarasinghe et al. 2020).

Nighttime light emissions are generally strongly correlated with GDP per capita (Henderson, Storeygard, and Weil 2012). The data are available at a very fine spatial resolution of approximately 1 square kilometer (30 arc seconds) and can therefore be aggregated at the level of Brazilian municipalities, our units of observation. Figure 1 shows the borders of those municipalities and of Brazilian states.

To construct the data set, NOAA processes daily images taken by US Department of Defense weather satellites that orbit the Earth 14 times per day. Each satellite observes every location on Earth every night at some point in time between 20:30 and 22:00. NOAA removes observations biased by strong sources of natural light (including in the summer months, when the sun sets late), light activity related to the northern and southern lights, and forest fires. Observations obscured by clouds are also excluded.

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[10] Specifically, the maximum likelihood estimator uses an instrumental variable strategy to impose some structure on the spatial dependence embedded in matrix W. It instruments for nighttime lights in first-degree neighbors (i.e., municipalities directly contiguous to an observation) by the logarithm of oil and gas revenues in second-degree neighbors (i.e., municipalities contiguous to first-degree neighbors). That instrument meets the exclusion restriction if oil price shocks, proxied by the logarithm of oil and gas revenues, that affect second-degree neighbors do not affect a given municipality otherwise than by generating economic activity that then spills over to direct neighbors. Table B4 shows that spillovers to indirect neighbors are statistically insignificant, lending credence to this assumption.

[11] In table B2 we show that the baseline results are unaffected if we cluster standard errors at the larger spatial resolution of micro- and mesoregions.

Figure 1. Brazilian municipal boundaries.

The filtered daily images are then averaged for the entire year, producing light intensity data ranging from 0 (no light) to 63, with higher values indicating greater luminosity. The result is a measure of nighttime light intensity that reflects only human economic activity.[12] Although it correlates positively with official GDP in our sample, the correlation is imperfect, as the coefficient of correlation in our sample amounts to just 0.30, which suggests that GDP captures only a part of the economic activity in our sample.

For our purposes, a useful feature of oil production in Brazil is that it is essentially done offshore. That implies that light emissions caused by oil production alone do not affect those of oil-producing municipalities. The risk of overglowing as a result of gas flaring is therefore limited. Moreover, as Caselli

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[12] See Henderson, Storeygard, and Weil (2012) for more technical information about the construction of the data set.

and Michael (2013) recall, offshore production can more easily be considered as exogenous. Our data on oil production come from Agencia Nacional de Petroleo (ANP; http://www.anp.gov.br/), which provides information on oil output, prices, and oil field locations on a monthly basis.[13] We use these data to determine the municipalities with oil fields, as well as their production shares. We define oil-producing municipalities as those with at least one oil field, or part of one, that entered production phase in 1992.

International oil and gas prices are taken from international financial statistics.[14] Figure 2 shows the locations of the oil-producing municipalities and the corresponding states.[15] Since oil-producing municipalities are defined as those that started oil production in 1992, we exclude all municipalities that did not exist in 1991 using data from IBGE and ANP. We follow Caselli and Michaels (2013) and assign offshore oil values to municipalities, using official shares called Percentuais Médios de Confrontação, which assign quotas to municipalities facing offshore oil fields.[16] It may be noted that oil-producing municipalities are located on the coast because they exploit offshore fields. Accordingly, gas flaring, which may artificially increase light emissions, is not a problem in our case.[17]

Population, in logarithm, is controlled for in all regressions, since it is strongly correlated with economic activity (Mamo, Bhattacharyya, and Moradi 2019). Data on annual municipality populations are obtained from intercensus population estimates provided by IBGE. Because the SDM approach requires a strongly balanced data set, missing municipal-year observations are filled in using linear interpolation to avoid dropping municipalities with missing years. Table 1 reports the summary statistics for our variables of interest.

To consider a reasonably homogenous sample, we focus on the nine oil-producing states, namely, Ceará (9 oil-producing municipalities), Rio Grande do Norte (16 municipalities), Alagoas (9 municipalities), Sergipe (19 municipalities), Bahia (26 municipalities), Espírito Santo (4 municipalities), Rio de Janeiro (5 municipalities), Sao Paulo (1 municipality), and Paraná (2 municipalities).[18]

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[13] Each oil field produces oil and natural gas, so we use "oil" to refer to both hydrocarbons throughout.

[14] It should be noted that some oil-producing municipalities are set to report zero oil output because they started producing after 1992.

[15] Fig. A2 (figs. A1, A2 are available online) zooms in on the oil-producing regions to give a better sense of the location of oil-producing municipalities.

[16] In app. A, we explain in detail how we construct the annual oil production series for each municipality.

[17] In addition, flaring has been historically concentrated in a group of five countries that do not include Brazil—Russia, Nigeria, Iran, Iraq, and Algeria—but that account for roughly half of all flaring worldwide. The United States has also quadrupled its flaring activity since 2010, driven by the shale boom (Calel and Mahdavi 2020).

[18] A list of oil-producing municipalities is provided in table A1.

Figure 2. Brazilian oil-producing states and municipalities.

The number and the size of Brazilian municipalities changed during the 1990s owing to divisions and mergers. We therefore restrict our sample to municipalities that existed in 1991 and exclude all of those that were established subsequently.[19] Our final baseline sample covers 1,940 municipalities, of which 91 produce oil. Admittedly, those municipalities represent a small fraction of the sample, and the results are identified using few observations. However, as Caselli and Michaels (2013) recall, this raises no conceptual issue as long as those municipalities are where the variation is. Moreover, we lose no oil-producing municipality, and table 1 shows that there is variation in both log(Revenues) and $W\Lambda$(Revenues), as their standard deviation is greater than their mean.

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[19] See Blakeslee and Fishman (2017) for a similar method. As a robustness check, we also use the full sample of the 2,065 municipalities in oil-producing states.

TABLE 1

SUMMARY STATISTICS

Variable	N	Mean	SD	Minimum	Maximum
Nighttime light emissions	42,680	4.990	9.248	0	63
W(Nighttime lights)	42,680	4.991	5.431	0	60.631
log(Revenues)	42,680	.966	4.439	0	28.611
$W\Lambda$(Revenues)	42,680	.966	2.270	0	20.048
log(Population)	42,680	9.705	1.128	6.578	16.285
Distance to oil municipality	42,680	249.886	176.887	0	724.385

Our period of analysis is 1992–2013. In all specifications, we cluster standard errors at the municipal level.

IV. Baseline Results

A. A First Look at the Data

Figure 3 plots average nighttime light emission levels, net of municipality, and year fixed effects against the international oil price separately for oil-producing (fig. 3*A*) and non-oil-producing (fig. 3*B*) municipalities. Figure 3*C* reports the results for all Brazilian municipalities combined.[20]

The figure shows that the price of oil correlates positively with nighttime light emissions in oil-producing municipalities and negatively in non-oil-producing municipalities. This finding suggests that while oil-producing municipalities benefit from higher prices, other municipalities suffer.

In both plots the nonparametric line suggests that the relationship is linear. Plotting all municipalities together, we see no relationship between the price of oil and nighttime light emissions, with the nonparametric line being flat. Accordingly, the previously depicted positive and negative relationships cancel out when combined.[21]

B. Findings

Table 2 reports the results from estimating equation (1) using various sample compositions and variable definitions. The baseline sample is restricted to municipalities in the nine oil-producing states. In column 1 oil production is set at 1992 levels, with the output of municipalities that started producing after 1992 set to zero. Column 1 reports a restricted version of equation (1) where ρ and α_2 are set to zero. In other words, column 1 reports the ordinary least

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[20] Specifically, we proceed in two steps. In the first step, we regress nighttime light emissions on municipality fixed effects and year fixed effects. In the second step, we plot the residuals of those regressions averaged over years to examine the relationship between the oil price and average annual nighttime light emissions.

[21] We obtain the same results when we use international gas prices (results not reported for brevity).

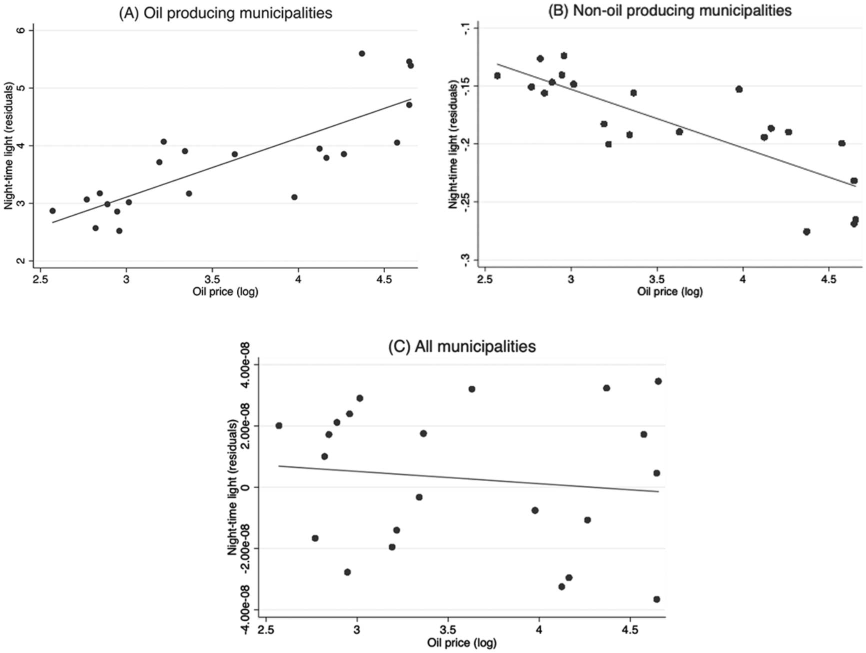

Figure 3. Effect of oil prices on economic activity. A color version of this figure is available online.

squares (OLS) estimates of equation (1). It shows that the coefficient α_1 of oil and gas revenues is positive and statistically significant at the 1% level. Thus, a 1% rise in oil and gas revenues increases economic activity, as measured by nighttime light emissions, by 0.675% in oil-producing municipalities. That finding is in line with previous studies reporting a positive effect of natural resources on economic activity in oil-producing areas (Black, McKinnish, and Sanders 2005; Michaels 2011; Aragón and Rud 2013; Allcot and Keniston 2018; Mamo, Bhattacharyya, and Moradi 2019; Gradstein and Klemp 2020).

Columns 2–4 explicitly tackle spatial spillovers by reporting the SDM estimates of equation (1), including the spatial lags of oil revenues and nighttime light variables.[22] In all of these models, the spatial autoregressive parameter ρ is positive and statistically significant beyond the 1% level, reflecting a strong correlation in economic activity across municipalities. Accordingly, a contemporaneous increase in economic activity in a neighboring municipality induces around a 0.17 luminosity point increase in economic activity in the municipality itself.

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[22] $W\Lambda$(Revenues) and log(Revenues) only weakly correlate. Their Pearson coefficient of correlation amounts to 0.069, and their covariance amounts to 0.697. Their correlation is therefore unlikely to have inflated standard errors and affected our main results.

TABLE 2

EFFECT OF OIL AND GAS REVENUES ON NIGHTTIME LIGHT EMISSIONS

	OLS	SDM			
	Baseline (1)	Baseline (2)	Subsample (3)	Oil Dummy (4)	Oil Dummy (5)
	A. Estimated Coefficients				
ln(Revenues)	.675***	.735***	.752***		
	(.216)	(.214)	(.215)		
$W\Lambda$(Revenues)		−.771**	−.791**		
		(.352)	(.345)		
ln(Oil price) × oil dummy				.796***	
				(.190)	
$W\Lambda$(Oil price × oil dummy)				−.721**	
				(.291)	
ln(Gas price) × oil dummy					.978***
					(.240)
$W\Lambda$(Gas price × oil dummy)					−.932**
					(.365)
W(Light)		.168***	.156***	.169***	.169***
		(.018)	(.018)	(.018)	(.018)
Number of observations	42,680	42,680	42,064	42,680	42,680
Number of municipalities	1,940	1,940	1,912	1,940	1,940
R^2	.476	.478	.247	.328	.326
ln(Population)	✓	✓	✓	✓	✓
Municipality fixed effect	✓	✓	✓	✓	✓
Year fixed effect	✓	✓	✓	✓	✓
	B. Direct and Indirect Effects from SDM				
Direct effect		.711***	.729***	.774***	.950***
		(.217)	(.218)	(.193)	(.244)
Indirect effect		−.791*	−.807*	−.707**	−.931**
		(.432)	(.423)	(.354)	(.458)
Total effect		.080	−.078	.068	.020
		(.529)	(.522)	(.451)	(.572)

Note. The dependent variable is mean nighttime light emission intensity. The sample is restricted to municipalities located in nine oil-producing states. In col. 1, oil-producing municipalities that started production after 1992 are set to zero. Column 3 excludes oil-producing municipalities that started production after 1992. Columns 4 and 5 replace oil production in col. 1 by a dummy indicating oil-producing municipalities that started production from 1992 onward. The method of estimation in col. 1 is ordinary least squares (OLS); in cols. 2–5, it is the spatial Durbin model (SDM) based on a spatial weight row-standardized contiguity matrix *W* that assigns 1 to municipalities sharing a common border. Robust standard errors are reported in parentheses and clustered at the municipal level. Panel B reports estimates of direct, indirect, and total effects from SDM, with standard errors computed by Monte Carlo standard errors using 100 replications (LeSage and Pace 2009).

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Column 2 reports the estimation of equation (1) on the baseline sample. The coefficient α_1 of oil and gas revenues remains positive and statistically significant at the 1% level. Its magnitude marginally increases to now range from 0.735 to 0.752. The key new insight is provided by the coefficient of the spatial lag of oil and gas revenues, α_2, which is negative and statistically significant at the 5% level, indicating that economic activity in neighboring municipalities expands by less than the average that would be expected from the positive spatial correlation pattern observed in nighttime light emissions previously indicated by autoregressive parameter ρ.

The magnitude of coefficient α_2 ranges from -0.771 to -0.791 but cannot be interpreted directly because of the spatial spillovers with all other municipalities. This is why panel B reports the estimates of the implied direct effect of oil and gas revenues within an oil-producing municipality, of the indirect average spillover effect in the neighboring municipalities, and of the total average effect, which is the sum of direct and indirect effects. The panel thus gives the quantitative significance of our effects. The direct effect of oil and gas revenues within oil-producing municipalities is positive and statistically significant. Its magnitude implies that a 10% increase in oil and gas revenues boosts economic activity by 0.07 luminosity points. With an average nighttime light emission of 4.99 luminosity points in our sample, that coefficient translates to an average 1.4% increase in economic activity in oil-producing municipalities. Put differently, a 1 standard deviation increase in oil and gas revenues raises economic activity in oil-producing municipalities by 3.2% or by 0.73 standard deviation.[23]

The indirect spillover effect in neighboring municipalities is negative and significant, suggesting that oil and gas revenues reduce economic activity in neighboring municipalities. Its magnitude implies that a 1 standard deviation increase in oil and gas revenues in its neighboring municipalities reduces economic activity in a municipality by 1.8%. Furthermore, the magnitude of the spillover effect is nearly the same as that of the direct effect. As a result, the total average effect is small and statistically insignificant, since the positive direct effect and negative indirect effect cancel each other out.

By considering all municipalities that had not started producing oil in 1992 as having received no revenues throughout the period—even though a municipality may have started production in the following year—our results may display an attenuation bias. As an alternative, in column 3 we estimate equation (1) on a subsample of municipalities that excludes those that started producing oil after 1992. The coefficients of oil and gas revenues and of their spatial lag both slightly increase in magnitude but keep their signs and significance levels. The magnitudes of the direct, indirect, and total average effects also increase, and their signs and levels of statistical significance similarly remain unchanged, showing that our baseline finding was not driven by our definition of the commencement of oil production.

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[23] One may remark that the magnitudes of the direct and indirect effects are close to those of α_1 and α_2, respectively. This finding suggests that the magnitude of the feedback from neighboring municipalities back to oil-producing municipalities is relatively small.

To address concerns of an attenuation bias due to measurement error, we replace oil production in column 4 with a dummy variable that takes a value of one if the municipality has produced oil since 1992 and multiply it by the international price of oil. The coefficients of oil and gas revenues and of their spatial lag remain stable in sign and significance, as do their associated direct, indirect, and total effects. Similarly, in column 5 our results remain when we multiply the dummy indicating oil-producing municipalities by the log of international gas prices.

Overall, our results suggest large negative spillover effects from oil and gas revenues. A 10% increase in these revenues reduces economic activity in neighboring municipalities by around 0.08 luminosity units on average. Ignoring those spillovers would give a biased picture of the total effect of oil and gas revenues on economic activity. While oil-producing municipalities seem to benefit from an increase in oil and gas revenues, neighboring oil-producing municipalities suffer from it. As a result, the aggregate effect of oil and gas revenues on economic activity is negligible, which may explain the contradictory findings of the literature on the resource curse at the macroeconomic level (Sachs and Warner 1995, 2001; Auty 2001; Alexeev and Conrad 2009).

C. Robustness Checks

In our baseline specification, we examine the effect of the sum of oil and gas revenues on nighttime light emissions. However, oil and gas revenues may affect the economy differently. In columns 1 and 2 of table 3, we therefore differentiate the effect of revenues generated by production of the two hydrocarbons. In both models, we still see a positive direct impact of oil and gas revenues on nighttime light emissions within producer municipalities, with neighboring municipalities bearing negative spillovers and the total effect remaining small and statistically insignificant.

Looking at the distribution of nighttime light emissions, we find that around 99% of observations lie at measured intensity levels between 0 and 54, with about 1% of observations taking the extreme values of 0 and 54 and above. To make sure that our findings are not driven by extreme observations, we winsorize these values by replacing them with the next-highest (next-lowest) observation. This ensures that all observations are used, and the effect of possibly spurious outliers is reduced. Column 2 of table 3 contains the results of a regression estimating equation (1) with winsorized nighttime light emission values. The main results do not differ: the direct effect of oil and gas revenues on economic activity is positive and significant within oil-producing municipalities, the spillover effect to neighboring municipalities is negative and quantitatively larger than the direct effect, and the overall effect is small and insignificant.

TABLE 3

EFFECT OF OIL AND GAS REVENUES ON NIGHTTIME LIGHT EMISSIONS—ALTERNATIVE SPECIFICATIONS

	Oil Production Only (1)	Gas Production Only (2)	Winsorizing Extreme Values (3)	Lagged Oil and Gas Revenues (4)	Add Dynamics (5)
	A. Estimated Coefficients				
ln(Oil revenues)	.702***				
	(.186)				
$W\Lambda$(Oil revenues)	−.582*				
	(.307)				
ln(Gas revenues)		.804***			
		(.231)			
$W\Lambda$(Gas revenues)		−.768**			
		(.374)			
ln(Revenues)			.737***		.204***
			(.213)		(.078)
$W\Lambda$(Revenues)			−.790**		−.112
			(.349)		(.114)
ln(Revenues), $t-1$				.764***	
				(.214)	
$W\Lambda$(Revenues), $t-1$				−.721**	
				(.353)	
W(Light)	.169***	.168***	.162***	.170***	.125***
	(.018)	(.018)	(.018)	(.018)	(.011)
Light, $t-1$					.793***
					(.013)
Number of observations	42,680	42,680	42,680	40,740	40,740
Number of municipalities	1,940	1,940	1,940	1,940	1,940
R^2	.287	.255	.265	.257	.963
ln(Population)	✓	✓	✓	✓	✓
Municipality fixed effect	✓	✓	✓	✓	✓
Year fixed effect	✓	✓	✓	✓	✓
	B. Direct and Indirect Effects from SDM				
Direct effect	.685***	.781***	.713***	.743***	.194***
	(.189)	(.235)	(.216)	(.216)	(.066)
Direct effect (long-run)					.945***
					(.365)
Indirect effect	−.567	−.778*	−.812*	−.711*	−.110
	(.370)	(.463)	(.425)	(.411)	(.134)
Indirect effect (long-run)					−.037
					(1.501)
Total effect	.118	.003	−.098	.032	.084
	(.462)	(.566)	(.517)	(.489)	(.148)
Total effect (long-run)					.908
					(1.717)

Note. The dependent variable is mean nighttime light emission intensity. The sample is restricted to municipalities in nine oil-producing states. All columns show the estimates of a spatial Durbin model (SDM) employing a row-standardized contiguity matrix. Estimates are based on a spatial weight contiguity matrix W that assigns 1 to municipalities sharing a common border. Columns 1 and 2 estimate the effect of oil and gas revenues, respectively, on nighttime light emissions. In col. 3, nighttime light data are winsorized by replacing extreme values with the next-highest/next-lowest observation. Column 4 employs the 1-year lagged hydrocarbon revenues as an explanatory variable. In col. 5, we add lagged nighttime lights. Robust standard errors are reported in parentheses and clustered at the municipal level. Panel B reports estimates of direct, indirect, and total effects from SDM, with standard errors computed by Monte Carlo standard errors using 100 replications (LeSage and Pace 2009).

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

It may be argued that the effect of oil and gas revenues materializes with a lag and that using its contemporaneous value underestimates the effect. To address this, in column 4 of table 3 we lagged oil revenues by 1 year. Again, the estimated coefficients and the associated effects do not change in sign, magnitude, or statistical significance, demonstrating that our baseline results were not driven by the lag structure.[24]

Equation (1) is static and does not take the inertia of economic activity into account. For that reason, we estimated a fully dynamic autoregressive SDM by adding the lagged dependent variable to the explanatory variables. The coefficient of lagged nighttime light emissions is positive and statistically significant. However, although the coefficient of oil revenues drops in size, it remains statistically significant. While the coefficient on spatial lagged oil revenues loses statistical significance at standard levels, it remains negative, and the estimated direct, indirect, and total effects remain unchanged. The long-run direct effect is larger than the short-run effect, suggesting that nighttime light emissions adjust very slowly, so that the direct effect of oil revenues on economic activity in oil-producing municipalities is around 400% larger in the long run.

Table 4 reports a series of robustness checks on our sample of municipalities. We have so far restricted our sample to the municipalities that existed throughout our period of study, thereby overlooking those that were established during the period. To make sure that this did not drive our baseline results, we include all municipalities in the nine oil-producing states, taking into account the ones that did not exist in 1991. Column 1 of table 4 shows that the estimated coefficient on oil and gas revenues becomes slightly larger, but the coefficient of its spatial lag increases by around 17%. The same is true for their associated estimated effects. All coefficients remain unchanged in sign and statistical significance.

Another way to make sure that our results are not driven by outliers is simply to drop extreme observations. We accordingly drop the top 10% of oil-producing municipalities in terms of production and estimate equation (1) anew.[25] The outcome of that estimation is reported in column 2 of table 4. Again, dropping large producers of oil does not affect the baseline results, in terms of either statistical or quantitative significance.[26]

To see whether the baseline results are driven by a specific period of time, we split the sample into two subperiods of equal length, specifically pre- and post-2003, and run a regression for each period separately. The two regressions are

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[24] We also check using a 2-year lag, and the results (reported in app. B) remain robust.

[25] The dropped oil municipalities are Açu, Areia Branca, Alagoinhas, Catu, Cabo Frio, Campos dos Goytacazes, Casimiro de Abreu, Macaé, and Quissamã.

[26] Additional robustness checks reported in app. B include dropping capital municipalities and light emissions above the 99th percentile. Our main results remain robust.

TABLE 4

EFFECT OF OIL REVENUES ON NIGHTTIME LIGHT EMISSIONS—SUBSAMPLES

	All Municipalities (1)	Drop Top 10% Oil Producers (2)	Subsample (1992–2002) (3)	Subsample (2003–13) (4)
	A. Estimated Coefficients			
ln(Revenues)	.749***	.775***	1.119***	.828**
	(.214)	(.237)	(.372)	(.385)
$W\Lambda$(Revenues)	−.902**	−.983***	−.768	−.807*
	(.352)	(.315)	(.485)	(.435)
W(Light)	.178***	.169***	.156***	.227***
	(.017)	(.018)	(.017)	(.020)
Number of observations	45,430	42,482	21,340	21,340
Number of municipalities	2,065	1,931	1,940	1,940
R^2	.248	.269	.096	.234
ln(Population)	✓	✓	✓	✓
Municipality fixed effect	✓	✓	✓	✓
Year fixed effect	✓	✓	✓	✓
	B. Direct and Indirect Effects from SDM			
Direct effect	.721***	.744***	1.099***	.797**
	(.217)	(.241)	(.376)	(.389)
Indirect effect	−.944**	−1.009**	−.759	−.837*
	(.441)	(.399)	(.545)	(.500)
Total effect	−.223	−.264	.340	−.040
	(.538)	(.520)	(.705)	(.683)

Note. The dependent variable is mean nighttime light emission intensity. The sample is restricted to municipalities located in nine oil-producing states. All columns show the estimates of a spatial Durbin model (SDM) employing a row-standardized contiguity matrix. Estimates are based on a spatial weight contiguity matrix W that assigns 1 to municipalities sharing a common border. In col. 1 we include all municipalities in the nine oil-producing states, including the ones that did not exist in 1991. Column 2 excludes the top 10% of oil-producing municipalities. Columns 3 and 4 restrict the sample period to two periods: 1992–2002 and 2003–13. Panel B reports estimates of direct, indirect, and total effects from SDM, with standard errors computed by Monte Carlo standard errors using 100 replications (LeSage and Pace 2009).

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

reported in columns 3 and 4 of table 4. The coefficient of oil and gas revenues is positive and statistically significant in both regressions. The spatial lag of oil and gas revenues is statistically significant for only the post-2003 period. This finding may be driven by the smaller size of the sample or suggest that spillovers essentially materialized in the second period. The estimated direct, indirect, and total effects for both samples follow the same patterns. In addition, the positive direct effect of oil revenues is always compensated by the negative spillover effect, so that the total effect is statistically insignificant, as in our baseline results.

Our identification strategy rests on the assumption that variations in oil and gas prices are exogenous to Brazil because the country is a price taker on world markets. To further address any concern related to endogeneity, we estimated two alternative versions of the baseline SDM, using two instrumental variable strategies. In the first version, we instrument nighttime lights observed in first-degree neighbors with the logarithm of oil and gas revenues occurring in second-degree neighbors.[27] In the second version, we instrument nighttime lights observed in first-degree neighbors with both the nighttime lights and the oil price shocks occurring in second-degree neighbors. The additional instrument in the second model (i.e., nighttime light in second-degree neighbors) resembles the approach used in time series to address autocorrelation in the dependent variable. The two-instruments strategy also allows us to test for overidentifying restrictions and validate the use of instrumental variable strategy.

The results are reported in columns 1 and 2 of table 5. In both models, our baseline results remain robust. Specifically, the direct effect of revenues remains positive and statistically significant at the 1% level, whereas the spillover effects are negative and statistically significant at the 1% level. Columns 3 and 4 check the robustness of our results to the inclusion of state-year fixed effects and state-specific time trends in the two-staged least squares model. The results show that our baseline results remain robust under these fixed effects.[28]

V. Extensions

A. How Spillovers Fade with Distance

We have so far taken the spatial dimension of spillovers into account by defining proximity as adjacency to a municipality, in line with the SDM. To go beyond that definition and see how far oil production in one municipality affects other municipalities, we complement our baseline results by using crow-fly distance to the nearest oil-producing municipality. To allow the relationship to be nonlinear, we define exposure to oil production in ring k as

$$\text{Exposure}_{isk} = \log(\text{Revenues}_{js}) \times \text{ring}_{ijk},$$

where ring_{ijk} is a dummy variable set to one if a municipality i in state s lies within a certain range k from oil-producing municipality j.

To define the rings' widths, we choose baseline distance cutoffs of 50, 100, 150, 200, 250, 300, and more than 300 kilometers.[29] Choosing 50 kilometers as the minimum baseline distance cutoff is fair for two reasons. First, the number of municipalities within 50 kilometers is small, which introduces more

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[27] We report evidence that that instrument meets the exclusion restriction in table B4.

[28] Note that the maximum likelihood technique used to estimate our SDM fails to converge in the presence of state-year fixed effects. This is not surprising given that the technique is less flexible when additional fixed effects or time trends are included.

[29] Distance thresholds are calculated according to the centroids of municipalities.

TABLE 5

ESTIMATION AND ALTERNATIVE FIXED EFFECTS

	(1)	(2)	(3)	(4)
	A. Nighttime Light			
ln(Revenues)	.985***	1.031***	.861***	.877***
	(.271)	(.235)	(.270)	(.245)
*W*Λ(Revenues)	−1.204**	−1.285***	−2.922***	−2.257***
	(.527)	(.462)	(.629)	(.510)
W(Light)	1.306**	1.514***	2.369***	1.898***
	(.645)	(.084)	(.211)	(.124)
Anderson-Rubin Wald, *F* (*p*-value)	.017			
Anderson-Rubin Wald, χ^2 (*p*-value)	.017			
Stock-Wright, Lagrange multiplier (*p*-value)	.010			
	B. First Stage for *W*(Light)			
*W2*Λ(Revenues)	−1.171**	−.779*	−.305	−.467
	(.601)	(.437)	(.510)	(.487)
W2(Light)		.883***	.736***	.813***
		(.024)	(.039)	(.028)
First-stage *F*-statistic	3.81	699.23	181.992	428.635
Kleibergen-Paap (*p*-value)	.04	.00	.00	.00
Hansen *J*-statistic	.00	.769	.169	.234
Number of observations	42,680	42,680	42,064	42,680
Number of municipalities	1,940	1,940	1,912	1,940
ln(Population)	✓	✓	✓	✓
Municipality fixed effect	✓	✓	✓	✓
Year fixed effect	✓	✓		✓
State-year fixed effect			✓	
State-specific time trend				✓

Note. The dependent variable is mean nighttime light intensity. The sample is restricted to municipalities located in the nine oil-producing states. The method of estimation is two-stage least squares with *W*(Light) instrumented by log(Revenues) in second-degree neighbors in col. 1 and by both the nighttime lights and the log(Revenues) in second-degree neighbors in cols. 2–4. *W* is the row-standardized contiguity matrix that assigns 1 to municipalities sharing a common border. *W2* is the row-standardized contiguity matrix that assigns 1 to municipalities sharing a common border with a direct neighbor of a municipality. Robust standard errors are reported in parentheses and clustered at the municipal level. Panel B reports the first-stage estimates.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

noise and reduces the power of the results. Second, given that oil-producing municipalities are moderately spatially clustered, employing distances less than 50 kilometers might capture the effect of the oil-producing municipality itself rather than the surrounding non-oil-producing areas. In particular, light emissions produced by the oil industry itself (i.e., gas flares or construction sites) may lead to overglow of nighttime light emissions due to gas flaring. Such overglow effects become smaller above 50 kilometers (Pinkovskiy 2017).[30]

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[30] Recall that oil production in Brazil is primarily from offshore fields, thereby limiting the effect of overglow across municipalities. However, as an additional robustness check, we also try cutoffs of 100, 200, 300, and more than 300 kilometers. The results remain unchanged (see app. B).

The spillover effect is then estimated by running the following regression:

$$Y_{ist} = \alpha_i + \vartheta_t + \beta_2 \log(\text{Revenues}_{ist}) + \sum_k \beta_k \text{Exposure}_{isk} + \varphi X_{ist} + \mu_{ist}, \tag{2}$$

where α_i and ϑ_t are municipality and year fixed effects, β_2 measures the direct effect of oil and gas revenues on economic activity in oil-producing municipalities (i.e., ring = 0 kilometers), and β_k captures the spillover effect of oil production on economic activity in municipalities located within a certain ring from oil-producing municipalities. Total spillover effects are therefore estimated by examining the aggregated effect of oil revenues within all rings at once, with each ring excluding the preceding one from its range. For instance, at the 100-kilometer radius, we excluded values from the 50-kilometer radius.

Table 6 presents the results from estimating equation (2). Since we include seven dummy variables to code distance to oil production, we adjust standard errors and report the family-wise error rate, following the method developed by Romano and Wolf (2005a, 2005b). The advantage of that method is that it uses a stepwise approach to take into account the probability of committing a type I error in the family of hypotheses. We report the adjusted *p*-values in square brackets beside the original standard errors. The direct effect of oil revenues on economic activity in oil-producing municipalities remains positive and statistically significant. As we move away, the effect becomes statistically insignificant in the 50- and 100-kilometer rings. We observe a negative effect of oil production that is statistically significant at the 5% level in the ring ranging from 100 to 150 kilometers. The effect is statistically insignificant at standard levels in the next three rings, specifically 150–200, 200–250, and 250–300 kilometers. In regions beyond 300 kilometers, the spillover effect of oil revenues is negative and weakly statistically significant at the 10% level.

Those findings refine the results of the SDM. They confirm that oil revenues generate both positive and negative effects. In addition, they suggest that those effects are unevenly distributed across space. The effect is positive in oil-producing municipalities but becomes negative, although statistically insignificant, in neighboring municipalities. The effect remains negative in municipalities located farther from oil-producing municipalities but turns statistically significant at the 5% level for those located between 100 and 150 kilometers from oil-producing municipalities. The effect is again statistically significant, but only at the 10% level, for municipalities located beyond 300 kilometers from an oil-producing municipality. It is also noticeable that the absolute magnitude of the negative effect is the smallest for municipalities within 50 kilometers of

TABLE 6

EFFECT OF OIL REVENUES ON ECONOMIC ACTIVITY—EXTENSIONS

	Ring (1)	Distance to Oil Municipality (2)	Distance to Oil Municipality (3)	Microregion (4)	Microregion (5)	Macroregion (6)
ln(Revenues)	.443**			.075	−3.279***	−5.555
	(.225)					
	[.045]			(1.306)	(1.058)	(7.800)
Exposure ≤ 50	−.066					
	(.296)					
	[.829]					
Exposure ≤ 100	−.260					
	(.351)					
	[.478]					
Exposure ≤ 150	−.604**					
	(.291)					
	[.050]					
Exposure ≤ 200	−.328					
	(.310)					
	[.378]					
Exposure ≤ 250	.278					
	(.332)					
	[.434]					
Exposure ≤ 300	−.075					
	(.200)					
	[.712]					
Exposure > 300	−.254*					
	(.137)					
	[.072]					
ln(Oil price)		2.048***				
		(.062)				
ln(Oil price) × distance to oil municipality		−.001***				
		(.000)				
ln(Gas price)			2.457***			
			(.076)			
ln(Gas price) × distance to oil municipality			−.001***			
			(.000)			
Number of observations	42,680	42,680	42,680	5,346	5,346	1,298
Number of municipalities/ microregions	1,940	1,940	1,940	243	243	59
R^2	.481	.478	.477	.592	.574	.673
ln(Population)	✓	✓	✓	✓	✓	✓
Municipality fixed effect	✓	✓	✓	✓	✓	✓
Year fixed effect	✓	✓	✓	✓	✓	✓

Note. The dependent variable is mean nighttime light intensity. The sample is restricted to municipalities located in nine oil-producing states. In all columns, oil municipalities that started production after 1992 are set to zero. The unit of observation is municipalities in cols. 1–3, microunits in cols. 4 and 5, and macrounits in col. 6. In col. 1, the spillover effects are estimated using the ring approach as described in the text. In col. 2, light pixels from oil municipalities are dropped. Robust standard errors reported in parentheses are clustered at the municipal level in cols. 1–3, the microlevel in cols. 4 and 5, and the macrolevel in col. 6. In col. 1, *p*-values adjusted to multiple-hypothesis testing are reported in brackets.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

an oil-producing municipality, suggesting that the negative spillovers from which they suffer are partly offset by positive spillovers. By contrast, negative spillovers dominate elsewhere, although their absolute magnitude tends to decrease as distance to oil production increases. This finding is in line with the presumption made in our theoretical framework that spillovers decrease with distance to oil production because transport costs dampen the effect of oil revenues on the relocation of tradeable goods and the migration of workers.

In column 2 of table 6, we follow Gradstein and Klemp's (2020) specification and replace the distance dummies by a continuous measure of crow-fly distance, measured in kilometers, which we interact with the international price of oil. The direct effect of the price on economic activity is positive and statistically significant at the 1% level. The estimated coefficient implies that a 10% increase in oil price raises economic activity by 0.20 percentage points in oil-producing municipalities—that is, when distance equals 0. The interaction effect is negative and significant at the 1% level, suggesting that the positive effect of oil fades as the distance from oil-producing municipalities increases.

Quantitatively, the average distance to an oil-producing municipality is 291 kilometers, so that the coefficient of the conditional effect implies that a 10% increase in the oil price raises economic activity in a non-oil-producing municipality within average distance of an oil-producing municipality by 0.18 points. This is 10% lower than the increase in economic activity in oil-producing municipalities.

This result replicates the finding of Gradstein and Klemp (2020), with the effect fading with distance but remaining positive. In contrast to our previous findings, the effect of oil production on economic activity never turns negative. The linear specification that Gradstein and Klemp (2020) use, and that we use here, therefore hides the negative spillovers observed with the SDM and the nonlinear model. The result is not confined to using the oil price. In fact, we obtain the same results in column 3 when interacting the distance to nearest oil-producing municipality with the international price of gas. The coefficients of log gas price and the interaction term are almost equal in magnitude to those in column 2.[31]

To further explore the spillover and general equilibrium effects of oil production, we follow Mamo, Bhattacharyya, and Moradi (2019) and redefine the unit of observation to correspond to higher administrative levels. By doing

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[31] For the sake of comparison, we also estimated the SDM without including the spatial lag of light emissions, *W*(Light). The outcome of the regression, reported in col. 2 of table B2, shows that the main findings are robust to not including that term. We thank an anonymous reviewer for that suggestion.

so, we define geographic units that internalize a part of the spillover effects. The larger the administrative unit, the larger the share of spillover effects that is internalized. We therefore first perform our analysis anew at the level of microregions—a grouping of economically integrated contiguous municipalities with similar geographic and productive characteristics—before estimating the equation at the macroregion level, the next-highest administrative level. Microregions echo the notion of local economies and have been widely used as units of analysis in the literature on how trade liberalization affects local labor markets in Brazil (Dix-Carneiro and Kovak 2015; Dix-Carneiro, Soares, and Ulyssea 2018). Microregions in our sample comprise eight municipalities on average and a maximum number of 41 with an average size of 5,000 square kilometers. We then perform the analysis again at the next administrative level: macroregions, which comprise 33 municipalities on average and have an average size of 22,000 square kilometers.

When estimating equation (1) on micro- and macroregions, we expect the coefficient of oil revenues to be smaller than in the baseline regressions, and perhaps even statistically insignificant, since the negative spillovers from oil and gas revenues may negate their positive direct effects.

Column 4 of table 6 reports the outcome of that estimation. In line with our previous results signaling the presence of negative spillovers, the coefficient of oil and gas revenues is now statistically insignificant. In the aggregate, the direct positive and negative spillover effects cancel out. Column 5 reports the results obtained using macroregions as our unit of observation. Unsurprisingly, the coefficient of interest remains statistically insignificant. In addition, it is now negative, suggesting that it internalizes a larger share of negative spillovers. Overall, the results of those extra regressions confirm that oil and gas revenues generate large and negative spatial spillovers on neighboring municipalities, rendering insignificant the total impact of oil revenues on economic activities in all municipalities. The results also explain why Caselli and Michaels (2013) find no statistically significant effect of oil revenues on a municipality's overall economic activity. This is because their study uses an aggregated unit of analysis that groups a number of municipalities within their 1970s historical boundaries.

Finally, we follow another specification, used by Mamo, Bhattacharyya, and Moradi (2019), to try to measure spillover effects alone. We do so by excluding nighttime light emission pixels originating in oil-producing municipalities from the aggregation by microregions before reestimating equation (1). Since activity from the municipalities that directly benefit from oil production is excluded, the coefficient of oil and gas revenues should capture only spillovers. In line with previous results, we expect the effect to be negative. The outcome of that regression is reported in column 6 and shows that the effect of oil revenues is indeed now negative and statistically significant. Those results therefore confirm the presence of negative spillovers from oil and gas revenues on economic activity in outlying regions.

B. Transmission Channels of Oil Revenues to Economic Activity

We now turn to the drivers behind the effect of oil revenues. To do so, we consider a series of alternative dependent variables that may all be affected by oil production.

Municipalities that neighbor an oil-producing municipality are also entitled to a small share of royalties if their land is used for oil postproduction operations (i.e., storage and transportation). Data on oil royalties (measured in real terms and expressed in US dollars) were obtained from Agencia Nacional de Petroleo for the period 1999–2013. Column 1 of table 7 shows the effect of oil revenues on total royalties received. The estimated coefficient of the direct effect is positive and statistically significant at the 1% level. The coefficient of its spatial lag is positive but much smaller in magnitude and significance. Quantitatively, a 10% increase in oil and gas revenues results in a 7% increase in royalties received by oil-producing municipalities, compared with a 1% increase in neighboring municipalities. The total effect is positive, statistically significant, and mostly driven by the direct effect, confirming that royalties are to a large extent a local phenomenon and have a limited spillover effect. The coefficient of the spatial lag of royalties is positive and significant but small in size, suggesting limited correlation between royalties across municipalities. Together with the finding that oil and gas revenues impose a negative spillover effect on the nighttime light emissions of non-oil-producing municipalities, this finding shows that the small royalties paid to non-oil-producing municipalities do not compensate for the overall negative impact on their economic outcomes.[32]

Column 2 examines the impact of oil revenues on populations and finds that they significantly increase the population of oil-producing municipalities but have no statistically significant impact on those of neighboring municipalities. A 10% increase in oil and gas revenues leads to 0.1% rise in the size of the population in oil-producing municipalities, but we find no evidence of a drain of workers from neighboring municipalities. Therefore, population movements from non-oil-producing to oil-producing municipalities are not the channel by which spillovers from oil and gas revenues are transmitted. As a result, the increase in population likely originates in nonneighboring municipalities.

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[32] The effect of increased royalties on neighboring municipalities could be further muted if royalties are partly diverted, as findings by Caselli and Michaels (2013) suggest.

TABLE 7

DRIVERS OF ECONOMIC ACTIVITY

	log(Royalties) (1)	log(Population) (2)	Real Wages, All Sectors (3)	Real Wages, Manufacturing (4)	Real Wages, Agriculture (5)	Real Wages, Service (6)	Local Prices (7)	ln(Crime) (8)
	A. Estimated Coefficients							
ln(Revenues)	.694***	.095***	65.952***	92.514*	−13.064	257.331*	20.297***	.308***
	(.149)	(.012)	(19.32)	(54.469)	(14.261)	(134.875)	(2.543)	(.041)
$W\Lambda$(Revenues)	.075	−.007	−26.188	−84.773**	−113.353***	−927.823***	−20.147**	.352***
	(.052)	(.027)	(22.876)	(42.542)	(17.402)	(233.099)	(9.722)	(.081)
W(Dependent variable)	.012	.152***	.111***	.063***	.141***	.218***	.046*	.168***
	(.008)	(.017)	(.015)	(.020)	(.018)	(.014)	(.025)	(.007)
Number of observations	29,100	42,680	23,286	18,888	20,472	23,280	31,977	42,680
Number of municipalities	1,940	1,940	1,940	1,574	1,706	1,940	1,683	1,940
R^2	.952	.478	.866	.096	.148	.359	.119	.054
ln(Population)	✓	✓	✓	✓	✓	✓	✓	✓
Municipality fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
Year fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
	B. Direct and Indirect Effects from SDM							
Direct effect	.695***	.095***	65.753***	91.711*	−16.865	218.044*	20.089***	.322***
	(.150)	(.012)	(19.314)	(54.610)	(14.125)	(134.620)	(2.509)	(.042)
Indirect effect	.081*	.011	−15.432	−73.906*	−125.665***	−1,022.539***	−20.950**	.454***
	(.052)	(.032)	(24.998)	(41.438)	(18.888)	(270.262)	(8.568)	(.099)
Total effect	.777***	.106***	50.303	17.805	−142.529***	−804.495***	−.860	.776***
	(.137)	(.035)	(30.364)	(68.856)	(22.680)	(306.618)	(8.506)	(.117)

Note. The dependent variable is log of royalties (in real terms) in col. 1, log of population size in col. 2, real average monthly wages in all sectors in col. 3, real average monthly wages in manufacturing in col. 4, real average monthly wages in agriculture in col. 5, real average monthly wages in the service sector in col. 6, the price of a given municipality's main locally produced crop in col. 7, and log of crime rate (per 100,000 inhabitants) in col. 8. The sample is restricted to municipalities located in nine oil-producing states. In all columns, hydrocarbon municipalities that started production after 1992 are set to zero. The method of estimation is a spatial Durbin model (SDM) employing a row-standardized contiguity matrix. Estimates are based on a spatial weight contiguity matrix W that assigns 1 to municipalities sharing a common border. Robust standard errors are reported in parentheses and clustered at the municipal level. Panel B reports estimates of direct, indirect, and total effects from SDM, with standard errors computed by Monte Carlo standard errors using 100 replications (LeSage and Pace 2009).

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

In columns 3–6 we test a specific prediction of the theoretical models developed by Moretti (2010) and Allcott and Keniston (2018). They argue that the rise in labor demand following resource booms will increase wages in resource-related sectors. In line with that assumption, Bartik et al. (2019) observe that wages rise in US counties after fracking begins. To examine this observation, we rely on wage data gathered by Registro Anual de Informaes Sociais, an official microdatabase for all registered formal workers during the period 2002–13. The wages are expressed in real terms, with nominal figures deflated by the consumer price index (Índice Nacional de Preços ao Consumidor) provided by Instituto de Pesquisa Econômica Aplicada (IPEA; http://www.ipea.gov.br/portal/index.php?option=com_content&Itemid=61) and converted to US dollars. Besides looking at overall wages, we explore heterogeneous effects by sector, namely, trade (defined as the sum of the manufacturing and agriculture sectors) and nontrade (defined as the service sector).

Column 3 uses the average wage in all sectors as the dependent variable. In that column, the coefficients of oil and gas revenues are positive and statistically significant, meaning that wages in oil-producing municipalities increase with oil and gas revenues. The spatial lag of the independent variable exhibits a negative but statistically insignificant coefficient, suggesting that there are no systematic spillovers for oil and gas revenues on wages in general. Similar results hold for wages in the manufacturing and service sectors (cols. 4 and 6, respectively), but there is no significant effect on wages in agriculture (col. 5). The coefficient for the direct effects indicates that a 10% increase in oil revenues increases total, manufacturing, and service wages in oil-producing municipalities by US$6.60, US$9.20, and US$21.80, respectively.

In neighboring municipalities, wages in manufacturing, agriculture, and services are adversely affected by oil revenues (cols. 4–6). The impact is particularly strong—both in magnitude and in statistical significance—for the service sector. Manufacturing, agriculture, and service wages in neighboring municipalities significantly decline by US$7.40, US$12.60, and US$102, respectively, for each 10% increase in oil revenues.

The total effect of oil revenues on wages is positive but statistically insignificant for the overall and manufacturing wages, meaning that the uptick in wages witnessed by oil-producing municipalities is offset by a decline in neighboring municipalities. For the service and agriculture sectors, the coefficients of the indirect effect are greater in size than the coefficients of the direct effect, so that the total effect is negative and statistically significant.

Column 7 examines the effect of oil and gas revenues on local prices. Following the reported increase in sectoral wages, we would expect a rise in demand for locally traded goods, which in turn increases their prices. Following

Aragón and Rud (2013), we test this proposition using the prices of locally produced agriculture goods. Local prices are based on the municipal agricultural production survey (Produção Agrícola Municipal) obtained from IPEA for the period 1992–2010 and expressed in US dollars in real terms. To determine the main agriculture crop and its price for each municipality, we follow Berman et al. (2017) and define it as the one with the highest total production value over the entire period (valued at 2,000 prices). We then divide the production value of the main crop by its production volume (measured in tons) to get the local crop price per ton. As expected, local prices in oil-producing municipalities increase with oil revenues but decline in neighboring municipalities. A 10% rise in oil and gas revenues increases local prices by US$2 per ton while reducing revenues in neighboring municipalities by almost the same amount.

Finally, in column 8 we analyzed the impact of oil and gas revenues on crime, which has been found to be one dimension of the resource curse (Couttenier, Grosjean, and Sangnier 2017). Crime rates are measured by the number of homicides per 100,000 inhabitants in a given year, obtained from IPEA for the period 1992–2013.[33] Previous studies identify two opposite effects of natural resources on criminal activities (see, e.g., Dube and Vargass 2013). On the one hand, higher royalties increase incomes, hence also increasing the incentives to engage in theft, expropriation, and illegal activities in general. This is referred to as the rapacity effect. On the other hand, a deteriorating economic situation reduces the opportunity costs of committing crimes and can therefore lead to a surge in criminal activity. In column 8, both oil and gas revenues and their spatial lag exhibit a positive coefficient. Although the coefficient of the spatial lag of oil and gas revenues is statistically insignificant at conventional levels, their marginal effect, reported in panel B of the table, is statistically significant at the 10% level. Accordingly, an increase in oil and gas revenues increases crime in both oil-producing and neighboring municipalities, suggesting that crime is one of the spillovers of oil and gas revenues. This is reminiscent of Bartik et al. (2019), who observed that the initiation of fracking in US counties led to an increase in violent crime.

Overall, the results suggest that oil revenues exhibit favorable and unfavorable effects and that the balance depends on the proximity of the municipality to oil production. In oil-producing municipalities, the favorable effects of oil revenues on royalties, wages, local prices, and populations outweigh the effect

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[33] The homicides rate is a good proxy for a municipality's crime rate, given the lack of data on other forms of nonviolent crime (i.e., property crimes such as theft, robbery, and burglary) at the municipal level. The same measure was used by Dix-Carneiro, Soares, and Ulyssea (2018) in estimating the impact of trade shocks on crime rates. We refer to their paper for more discussion on the high correlation between homicides rates and other types of crime at the state level.

of unfavorable spillovers found in the proliferation of criminal activity. As a result, we see a positive effect on overall economic activity. In neighboring, non-oil-producing municipalities, the severe decline in wages and local prices is amplified by a corresponding increase in crime rates. We therefore see a negative effect in overall economic activity.

Those findings are consistent with a model where a rise in oil and gas revenues in oil-producing municipalities increases demand for both tradeable and nontradeable goods and attracts scarce resources to those municipalities. As a result, oil and gas revenues reduce the productive capacity of other municipalities, a decline that is magnified by an increase in crime.

VI. Conclusion

We study spatial distribution of the effect of oil and gas revenues on Brazilian municipalities. Using variations in the international prices of oil and gas to establish causality, we confirm that oil and gas revenues increase economic activity in oil-producing municipalities. However, we also observe that oil and gas revenues in a municipality impose a negative spillover effect on neighboring municipalities, with both gas and oil revenues contributing to such effects. Moreover, our main finding is not driven by outliers or sample selection and is robust to various specifications that allow for a dynamic relationship.

The finding that oil and gas revenues benefit oil-producing municipalities is in line with the within-country literature, which emphasizes that areas endowed with natural resources tend to benefit from them. In that respect, we show that oil-producing municipalities do not suffer from a resource curse, whereas neighboring municipalities do. Accordingly, oil-producing municipalities impose a negative spillover on their neighbors. We observe that those spillovers become larger, relative to direct effects, as a municipality's distance from oil production increases, and they dominate in municipalities located more than 150 kilometers from oil activities.

When studying how oil and gas revenues affect non-oil-producing municipalities, we confirm that oil and gas revenues increase royalties in neighboring municipalities. They also increase population, real wages (especially in the manufacturing sector, as well as in agriculture and services), local prices, and crime. Moreover, we observe negative spillover effects of oil and gas revenues on wages and prices and positive spillovers on crime in neighboring municipalities.

One consequence of negative spillovers of oil and gas revenues on non-oil-producing municipalities is that the sum of direct and spillover effects is close to zero. Accordingly, we observe no effect of oil and gas revenues on economic activity at higher levels of aggregation, as direct and spillover effects cancel out. This finding may explain the conflicting results in the cross-country literature.

In any case, our results point to an uneven geographic distribution of the balance between the benefits and costs of natural resources. Oil-producing municipalities and municipalities distant from oil production are affected in opposite ways by oil and gas prices, and nonproducers may lose from oil production. We also find that oil revenues affect wages and prices, which hints at possible distributive effects between factors of production. Those findings suggest that some form of redistribution may be necessary, whether between municipalities or individuals. However, a full assessment of the need for redistribution and the form it should take requires a broader investigation of the economic and social consequences of oil and gas production including in the long run. Future research is therefore warranted.

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