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Too Much of a Good Thing: Accelerated Growth and Crime

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Abstract:

We document that oil-producing areas of Brazil experienced increases in crime during the period of increased economic growth driven by the 2000s oil boom. This challenges the understanding that the impact of income shocks on crime is driven primarily by the legal status of the market in question. Offshore oil production, refining, and distribution in Brazil are concentrated in large firms, without scope for income contestability. We show that various equilibrium effects of the Shock - such as increased inequality, urbanization, illegal goods presence, and deterioration in public goods provision - are likely to have contributed to the increase in crime.

Keywords: Crime, Oil, Income, Brazil

JEL Codes: H75, K42, Q34

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1 Introduction

The link between local income shocks and crime has been a traditional topic in the economics of crime literature. Most of this research has focused on how local labor market conditions affect crime rates, relying on the classic interpretation from Becker (1968) and Ehrlich (1971) that increases in local wages and employment should raise the opportunity cost of crime, therefore reducing individual-level incentives for criminal participation. Empirical papers in this literature have relied for identification on different types of Bartik shocks, trade liberalization episodes and booms to specific markets, and have consistently identified that improvements in local labor market conditions are associated with reductions in crime rates (Raphael and Winter-Ebmer, 2001; Gould, Weinberg and Mustard, 2002; Dix-Carneiro, Soares and Ulyssea, 2018; Axbard, Poulsen and Tonolen, 2019).

More recently, another literature has argued that the nature of the income shock—whether legal or illegal, or more or less contestable—is essential for a complete understanding of the potential effects of different types of economic shocks on crime rates. This literature has explored shocks to illegal markets and also to commodities with different degrees of enforcement of property rights, showing a causal relationship between positive shocks to rents in contestable markets and increases in violence, opposite, as should expected, to the relationship documented by the literature on legal labor markets (Angrist and Kugler, 2008; Dube and Vargas, 2013; Chimeli and Soares, 2017; Idrobo, Mejía and Tribin, 2014).

In this paper, we document an episode of local economic growth that was accompanied by increases in crime and violence. The peculiar aspect of this episode comes from the fact that the growth was driven by a shock to a heavily regulated market with strongly enforced property rights. This challenges the understanding that the legal status of a market is the only relevant intervening factor in the relationship between local economic shocks and crime rates.

We focus on the 2000s oil boom and on the main coastal oil-producing states of Brazil. We show that municipalities with oil wells displayed similar growth trends to other municipalities before international oil prices started sky-rocketing in the early years of that decade. During the boom, GDP growth in oil-producing municipalities was close to 100% higher than that in non-producing municipalities. This was the result of a combination of expansions in production in the petrochemical sector and subsidiary activities, expanded demand for local services, and royalty payments to local governments. These results confirm the patterns documented by Cavalcanti, da Mata and Toscani (2019), who show that the oil boom had large positive spillovers on local economies, increasing formal employment, the incidence of higher value-added activities, and urbanization. Nevertheless, we show that these same municipalities experienced large increases in crime during the boom, despite the significant increases in legal economic activity.

Rights to oil extraction in Brazil are controlled by the state, which can auction wells for exploration by private companies or the state-owned giant Petrobras. All the relevant production sites in the country are off-shore wells requiring sophisticated technology and sizeable amounts of capital. Extraction has been historically dominated by Petrobras and other oil giants such as BP, Chevron, and Texaco, while refining is still a *de facto* monopoly of Petrobras. So, in no way it can be argued that production, refining, or distribution of crude oil in the country are contestable markets with poorly enforced property rights.

Based on this realization, in order to rationalize the increase in violence observed during the oil boom, we turn our attention to potential general equilibrium effects of this type of local shock. We consider two such effects: (i) changes in the relative returns to capital vs. labor; and (ii) side effects of rapid economic growth, as related to urbanization, demand for illegal goods, and provision of public goods.

First, a rapid increase in the price of oil may change the relative returns to, and size of, capital-intensive and labor-intensive sectors, thus making unskilled workers worse-off, either in absolute or relative terms (when compared to capital owners). As shown in Dal-Bó and Dal-Bó (2011) for the case of a 2×2 small open economy, a positive shock to the price of capital-intensive sectors (such as oil in Brazil) can expand the capital-intensive sector and contract the labor-intensive one. The former, however, may not absorb all the labor released by the later, or may do so at relatively low wage levels. This worsening of the relative labor market conditions of unskilled workers may reduce the opportunity cost of engaging in criminal activities.

Second, a long tradition in criminology posits that environmental factors associated with social control may also affect equilibrium crime rates (see, for example, the influential essay by Wilson and Kelling, 1982). Rapid population and income growth may increase density and anonymity, raise the demand for illegal goods such as drugs, and put pressure on the provision of public goods at a pace that the state may be unable to respond to in the short term. In reality, previous research has suggested that the sizeable royalties received by oil-producing municipalities during the boom period do not seem to have translated into significant increases in public good provision (Monteiro and Ferraz, 2010; Caselli and Michaels, 2013).

Focusing on these potential mechanisms, we first show that oil-producing municipalities experienced increases in labor market inequality (formal) during the oil boom. Also, there was a positive impact on both the skilled-unskilled and the white-blue collar wage gaps (Adamczyk, Ehrl and Monasterio, 2022). Finally, estimates suggest a significant reduction in the ratio between formal wage payroll and local GDP, indicating increases in the capital share in local income. Together, these results give support to the logic of the mechanism proposed by Dal-Bó and Dal-Bó (2011).

We also show that oil-producing municipalities experienced accelerated population growth and urbanization during this period, accompanied by an increased presence of illegal drugs (proxied by mortality due to overdoses). At the same time, despite increases in revenue, there was no noticeable improvement in the provision of public goods. The boom period, specifically, registers significant reductions in secondary net enrollment rates. Secondary enrollment refers to teenagers, the group most likely to be involved in crime and to join drug-trafficking gangs in Brazil (Carvalho and Soares, 2016). Most of the other indicators of public good provision per capita, despite non-significant results, also point to deteriorations in coverage.

Even though our results do not provide unmistakable evidence of one particularly dominant force, the overall pattern paints a picture remarkably consistent with the observed increase in violence. General equilibrium effects coming from changes in the relative price of labor and capital, deterioration in public good coverage, and intensified presence of illegal drugs—in a context of increased anonymity due to accelerated population growth and urbanization, and with more teenagers out of school—are likely to be important ingredients in this story. Despite increased revenue in the hands of local governments, public good provision does not seem to have been able to respond at the pace required by local urban growth. The possibility of increases in corruption and pork-barrel politics suggested by other authors in this same setting may also have been a contributing factor to this sluggish response (Monteiro and Ferraz, 2010; Caselli and Michaels, 2013).

Our empirical strategy combines propensity score weighting with a difference-in-differences specification. We define two treatments, corresponding to the interaction of a dummy indicating the local presence of an oil well in a municipality with two dummies identifying the oil boom and bust periods (2004 to 2013 and 2014 to 2016, respectively). We provide evidence on the validity of the difference-in-differences identifying assumption by also presenting event-study results. Our qualitative results are virtually identical in an alternative specification in which we replace these two treatment variables by the interaction of the lagged international price of oil (WTI price) with the local presence of an oil well. We present all results using both specifications. Our data cover the period from 1997 to 2016 and include variables drawn from the Ministry of Health's DATASUS dataset, the Ministry of Labor's RAIS dataset, the Brazilian Census Bureau (IBGE), the system of national accounts, state police records, and the National Oil Agency (ANP), among others.

As mentioned before, our paper is closely related to the literature on the effect of different types of local economic shocks—legal and illegal—on crime. This literature has mostly focused on the nature of the economic shock itself as the main driver of the relationship between income gains and the incidence of crime and violence (Angrist and Kugler, 2008; Idrobo, Mejía and Tribin, 2014; Mastrobuoni and Pinotti, 2015; Chimeli and Soares, 2017; Dix-Carneiro, Soares and Ulyssea, 2018; Dell, Feigenberg and Teshima, 2019; Axbard, Poulsen and Tonolen, 2019; Castillo, Mejía and Restrepo, 2020; Britto, Pinotti and Sampaio, 2022). We argue, instead, that local income shocks may change the relative costs and benefits of crime in ways that are not directly related to the nature of the income shock, but rather to its potential indirect effects on the local economic environment Ferraz, Soares and Vargas (2022).

In substantive terms, our paper is probably most similar to Baires and Dinarte (2017), who show how improvements in public infrastructure can sometimes lead to increases in crime. They analyze the construction of a transnational highway in El Salvador and present evidence that smaller municipalities along the path of construction of the highway, which greatly benefited economically from the increased market access, experienced increases in extortions and homicides, suggesting also the emergence of new opportunities for illegal activities and an increased presence of organized crime. Similar evidence is presented for the case of civil conflict and rural road constructions in Colombia by Moreno, Gallego and Vargas (2020). But, differently from Baires and Dinarte (2017) and Moreno, Gallego and Vargas (2020), we explore a simple income shock, rather than increased market access. The latter is likely to also affect the accessibility of the respective areas to criminal organized crime groups that already operated in larger cities.

From the perspective of the focus on oil production, our work relates to that of Dube and Vargas (2013) and James and Smith (2017). Our institutional context and interpretation, though, are very different from theirs. Dube and Vargas (2013) analyze the opposing effects of oil and coffee price shocks on civil conflict in Colombia. They argue that the positive effect of oil prices on civil conflict derives from the contestability of the economic rents associated with oil production. As we argued before, oil extraction, refining, and distribution in Brazil are under heavy regulation and there is no scope for contestability in these markets, since there is *de facto* no market operating outside of the official one. James and Smith (2017), in turn, analyze the expansion in production of tight oil and shale gas in the US during the 2000s, documenting significant increases in property and violent crime in shale-rich counties. They also show that inequality increased in these areas during this period and provide suggestive complementary evidence for North Dakota indicating that shale-rich counties received a disproportionate number of domestic immigrants with criminal records (registered sex offenders). Street (2020) complements this evidence by showing that there is actually a reduction in criminal participation among previous residents in North Dakota, confirming the key role of compositional changes in the fracking context in the US. We propose alternative mechanisms for the increased violence, including changes in the relative return to labor and capital and social disorganization brought about by accelerated population and income growth. We show that, in our setting, there is no evidence of significant changes in population composition.

From a broader perspective, we argue that the net effect of local income shocks on crime, within an environment of imperfect enforcement, depends on the combination of legal and illegal opportunities that it generates, both directly and indirectly. An income shock to a legal market—such as the oil market in Brazil—can improve legal opportunities through spillover effects on the local economy, but it can also increase illegal opportunities through increased social anonymity, more local income available for violent appropriation, and expanded demand for illegal goods such as drugs. So, even a positive legal income shock, if not followed by increased enforcement and provision of public goods, may, in net terms, increase the relative benefits from engaging in crime for some fraction of the population. Our paper adds to the literature by showing that this indirect effect on the local economic environment can indeed be empirically relevant.

The remainder of the paper is organized as follows. Section 2 provides a background of the oil industry and recent trends in crime and violence in Brazil. Section 3 presents the data. Section 4 discusses our empirical strategy. Section 5 presents our main results. Finally, Section 6 concludes the paper.

2 Institutional Background

2.1 Oil in Brazil

Until the early 1990s, Brazil accounted for less than 1.5% of global oil production (data from the US Energy Information Administration). Following the end of the state monopoly in oil extraction and refining in 1997, the discovery of large offshore oil fields, and the rise in the international price of oil during the 2000s, the country more than tripled its production.[1] By 2020, Brazil had become the 8^{th} oil producer in the world, accounting for 4% of the global output.

The vast majority of the country's oil production comes from offshore wells concen-

[1]Since its foundation in 1953, *Petrobras*, the Brazilian state-owned oil company, was the only firm allowed to extract oil in the country. The enactment of the *Oil Law* (see https://www.planalto.gov.br/ccivil_03/leis/l9478.htm) in 1997 ended this monopoly.

trated in the coastal states of the Southeastern region (Monteiro and Ferraz, 2010; Caselli and Michaels, 2013). Even within this region, production is highly concentrated in relatively few municipalities. For example, there were only 13 (out of 815) municipalities extracting oil in the Southeastern coastal states of São Paulo, Rio de Janeiro, and Espírito Santo in 2013. These few municipalities together accounted for 90.84% of the country's oil production in that same year.

Oil-producing municipalities were greatly affected by the swings in international oil prices of the 2000s and early 2010s. Despite the subprime crisis and the global recession in 2008, international oil prices rose by more than 210% between 2004 and 2013. After reaching \$97 per barrel in 2013, prices then collapsed to only \$43 per barrel already in 2016 (annual average spot prices from the *World Texas Intermediate* (WTI) series). Oil production in the Brazilian Southeastern coast increased both during the boom and bust periods. Total production went from around 1.2 million barrels per day in 2004 to almost 2.5 million in 2016, whereas oil production in coastal states in other regions remained roughly constant (see Figure A.1). As the oil industry became more important for local economies, the impact of oil price shocks also became more relevant.

Concomitantly with the growth in oil production, municipalities were also impacted by fiscal windfalls during this period. According to Brazilian law, companies extracting oil are required to pay royalties to central and local governments, in particular the ones where extraction takes place. In spite of existing since 1953, royalties payments became a significant source of income to local governments only after the enactment of the *Oil Law* in 1997 and the expansion in offshore drilling during the 2000s (Cavalcanti, da Mata and Toscani, 2019). According to the law, oil companies must pay up to 10% of their gross revenue as royalties. The Brazilian oil and gas regulatory agency (*Agência Nacional do Petróleo, Gás Natural e Biocombustíveis*) follows a set of objective rules establishing how much in royalties each sphere of government should receive (described in detail in Monteiro and Ferraz, 2010 and Caselli and Michaels, 2013). Municipalities typically receive a significant share of these resources: for example, 34.3% of the R\$23.4 billion disbursed in 2018 (\$6.4 billion). Monteiro and Ferraz (2010) and Caselli and Michaels (2013) document that, nevertheless, this increase in revenues from royalties did not translate into improved public good provision in oil-producing municipalities. We revisit this evidence in our results section.

2.2 Crime and Violence in Brazil

According to the World Bank, Brazil recorded more than 43,000 intentional homicides in 2010, giving the country the second-highest worldwide death count by homicides (with

22.1 homicides per 100,000 inhabitants, the country ranked 19^{th} in terms of homicide rates). Though historically the majority of homicides occurred in larger cities, the last few decades have witnessed a process of increased violence in smaller and medium-sized cities, while at the same time some larger urban centers made substantial progress in fighting crime and violence (Cerqueira, 2010). Figure 1 presents the distribution of homicide rates in Brazil in 2010, illustrating that violence is an issue in various areas of the country.

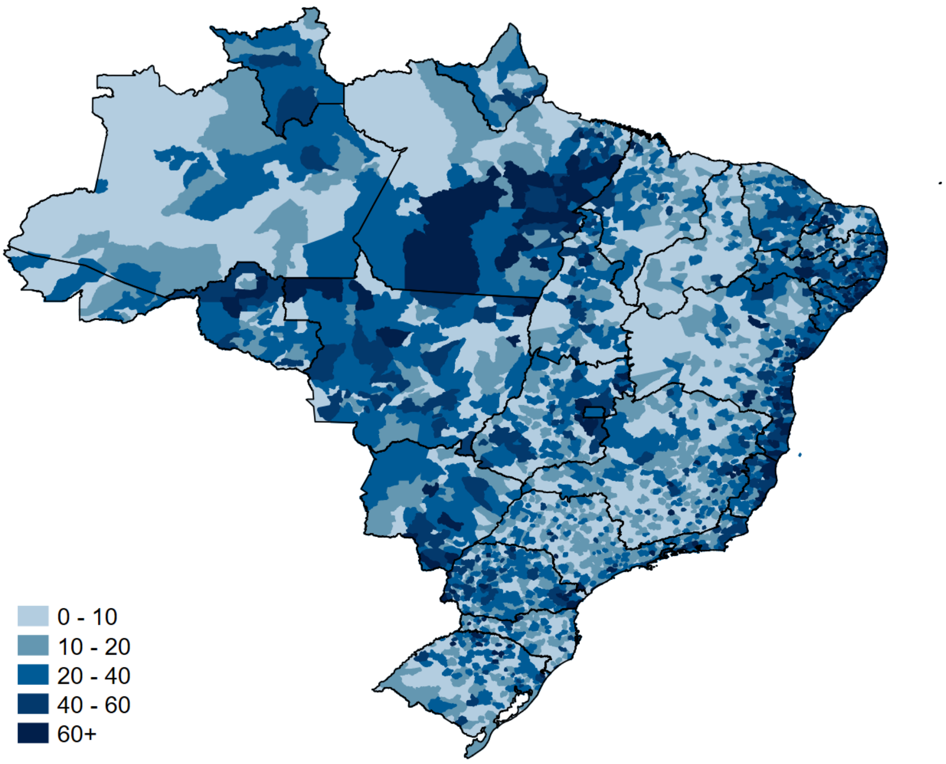

FIGURE 1: HOMICIDES PER 100,000 INHABITANTS IN 2010

The figure shows, in particular, a large variation in homicide rates even within states. In the state of São Paulo, which accounts for over a fifth of the country's population, despite a median homicide rate of only 4.74, the top 10% municipalities had more than 20 homicides per $100,000$ inhabitants in 2010. This degree of heterogeneity is an important dimension that we explore in our empirical exercise.

Differently from countries with lower levels of violence, where homicides are typically the result of disputes of a personal nature among individuals who oftentimes know each other, homicides in Brazil bear a close relationship with common economic crimes. Dix-Carneiro, Soares and Ulyssea (2018), for example, document a very high correlation between homicides and property crimes across municipalities and time in Brazil. They also discuss ethnographic evidence suggesting that 40% of the homicides in the country—at the very least, but likely much more—are connected to drug trafficking and common economic crimes such as robberies. For this reason, and because they are recorded more consistently across states over our sample period, we focus on homicides as our measure of the occurrence of crime and violence.

3 Data

We collect data from several sources and build a panel of local economies in Brazil from 1997 to 2016. We focus on the coastal states of Brazil's Southeastern region—São Paulo, Rio de Janeiro, and Espírito Santo—which accounted for more than 90% of the country's oil production in 2013. Also, since a large number of municipalities were created in the 1990s and early 2000s, we use Minimum Comparable Areas (*Áreas Mínimas Comparáveis - AMCs*) as units of observation. This allows for the comparison of the same geographic areas over time and is common practice in the literature using municipality-level data in Brazil (Reis et al., 2008).

One of our main sources of data is the Brazilian National Oil Agency, *Agência Nacional do Petróleo, Gás Natural e Biocombustíveis* (ANP). We obtain from ANP data on the universe of onshore and offshore oil wells drilled since 1941, with respective location and drilling date[2]. We then use the presence of a well that produced at some point in time as a proxy for the local presence of the oil industry, regardless of whether the well was actually active or inactive during the 1997-2016 period. By using well presence rather than production status, we try to minimize potential endogeneity issues associated with production decisions.

We also make use of data from the *Relação Anual de Informações Sociais* (RAIS), a yearly matched employer-employee administrative dataset from the Brazilian Ministry of Labor providing information on the universe of formal labor contracts in the country. In addition, we construct some socioeconomic and demographic variables using 2000 census microdata.

Finally, data on local GDP and population estimates come from the *Instituto Brasileiro de Geografia e Estatística* (IBGE), the Brazilian Census Bureau, whereas deaths by homicide and other causes come from the Brazilian Ministry of Health's administrative records (DATASUS, *Sistema de Informações sobre Mortalidade* - SIM). Data on municipality area covered with urban infrastructure come from *MapBiomas*, an interdisciplinary initiative on the measurement of the patterns of land use in Brazil. We also collect data on local public expenditures and revenues from FINBRA, a database from the Brazilian National

[2]As Cavalcanti, da Mata and Toscani (2019), we allocate onshore wells to the AMCs where they are located and allocate offshore wells to the AMCs whose boundaries are closest to the well.

Treasury, and data on specific types of crimes and apprehension of weapons and drugs from the state polices of Rio de Janeiro and São Paulo.

3.1 Descriptive Statistics

Our sample consists of $14,040$ AMC$-$year observations, corresponding to 702 distinct AMCs during the 1997-2016 period. Table 1 reports basic summary statistics separately for AMCs that had an oil well and AMCs without wells. From now on, we call them simply "oil" and "non-oil" AMCs, respectively. Panel A presents various socioeconomic characteristics calculated from the 2000 census. It shows that, in terms of household income, oil AMCs were initially poorer and slightly more unequal when compared to non-oil municipalities. They also had a substantially lower fraction of employment in manufacturing. The share of workers in the oil and gas sector was 6 times higher than in other municipalities, but still, at that point, very small in absolute terms.

In Panel B, we present data on homicides, GDP per capita, and population, broken down into three sub-periods: the pre-boom period (1997-2003), the boom period (2004-2013), and the bust period (2014-2016).

Interestingly, oil municipalities already had GDP per capita substantially higher than non-oil municipalities before the boom, despite the fact that average household income as measured from the census was substantially lower. This indicates that a substantial part of the income produced in these areas, most likely associated with oil, was appropriated by capital and not translated into labor earnings. This difference in GDP per capita increases dramatically during the boom period and shrinks again during the bust.

In terms of violence, non-oil regions were already somewhat safer before the oil boom, but this difference also increased dramatically during the boom, in this case not receding back during the bust period. In the later period, homicide rates in oil AMCs reach levels more than 2.3 times higher than those observed in non-oil AMCs. Population dynamics displayed a similar pattern, with large and consistent increases in the relative population of oil AMCs throughout the whole period.

We complement this discussion by showing that the relative changes in GDP and homicide rates across oil and non-oil AMCs closely track the movements in the international price of oil. In Figure 2, we present the difference in GDP across oil and non-oil AMCs in the left axis and the spot price of oil (WTI) in the right axis. We first calculate the weighted average of GDP within the sets of oil and non-oil AMCs. Then, we normalize these weighted averages by their 2003 values and compute the difference between oil and non-oil areas, so that the 2003 value is zero and other years indicate the relative increase in GDP in oil AMCs. The figure shows that the normalized GDP difference

TABLE 1: SUMMARY STATISTICS

	Non-oil AMCs ($N = 686$)		Oil-rich AMCs ($N = 16$)	
	Mean	Std. Dev.	Mean	Std. Dev.
Panel A: 2000 Population Census characteristics				
- Household income per capita (2018 BRL)	12,949	[4,713]	9,331	[2,181]
- Fraction of individuals below the poverty line	0.136	[0.066]	0.233	[0.057]
- Gini coefficient	0.534	[0.042]	0.567	[0.025]
- Fraction of young individuals	0.337	[0.016]	0.328	[0.012]
- Average years of schooling	5.3	[0.7]	4.5	[0.5]
- Fraction of employed in the manufacturing sector	0.184	[0.082]	0.095	[0.036]
- Fraction of employed in the oil and gas sector	0.001	[0.006]	0.006	[0.006]
Panel B: Annual data				
Pre-boom period (1997-2003)				
- Homicides per 100,000 inhabitants	37.23	[27.0]	41.18	[20.7]
- GDP per capita (2018 BRL)	35,496	[27,705]	50,597	[40,956]
- Population	52,884	[123,045]	86,484	[97,370]
Boom period (2004-2013)				
- Homicides per 100,000 inhabitants	22.93	[18.5]	45.09	[17.3]
- GDP per capita (2018 BRL)	41,259	[31,711]	90,713	[72,151]
- Population	59,875	[138,239]	105,773	[110,095]
Bust period (2014-2016)				
- Homicides per 100,000 inhabitants	18.89	[16.1]	44.42	[16.3]
- GDP per capita (2018 BRL)	42,177	[30,808]	69,279	[52,309]
- Population	64,261	[145,289]	120,642	[122,576]

Notes: Panel A reports the cross-section averages within non-oil and oil groups according to the 2000 Population Census. In Panel B we calculate the averages within each group with annual observations. All averages are weighted by AMC's population in 2003, except for population itself in Panel B. The fraction of individuals below the poverty line is defined as the fraction of individuals that earned less than one-fourth of the minimum wage per month. We also define the fraction of young individuals as the proportion of individuals in the 20-39 years old interval.

follows closely the WTI curve. The GDP difference grows from 0 to more than 80 during the 2004-2013 period, following an increase of more than 200% in oil prices. After 2014, both variables experience a pronounced decline, suggesting that local income changes in oil regions were directly affected by the exogenous movements in international oil prices.

Figure 3 presents an analogous descriptive exercise for homicide rates. The left axis now measures the normalized difference in homicide rates across oil and non-oil AMCs. As in the previous figure, the homicide rate difference across oil and non-oil areas follows closely the oil price series. The only noticeable change in relation to the previous figure is that the reduction in homicides during the bust period is very mild when compared to

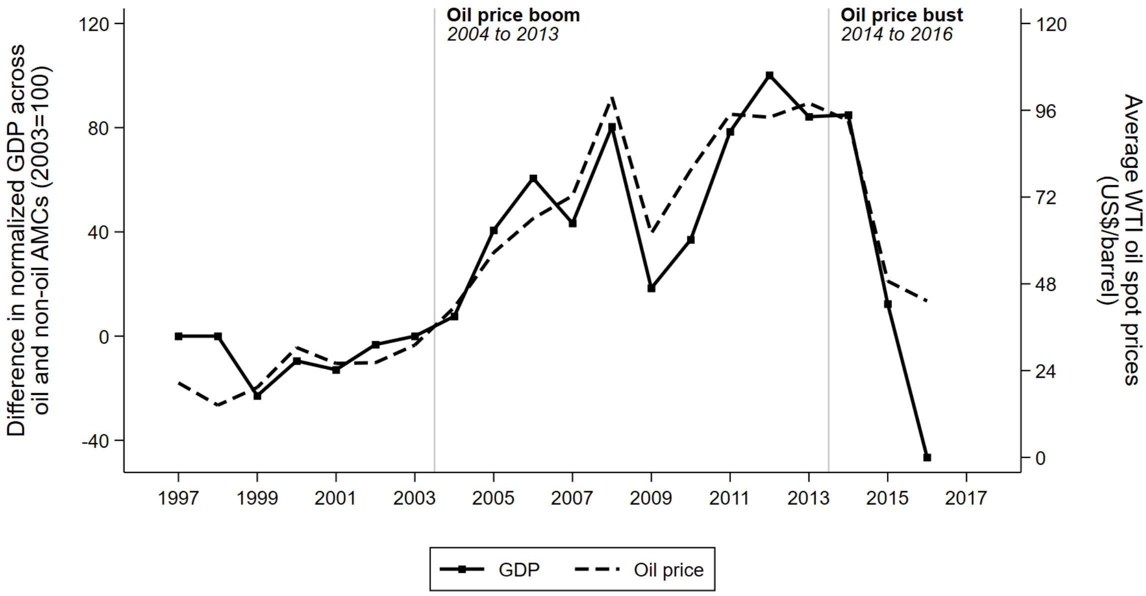

FIGURE 2: LOCAL GDP AND OIL PRICES

the reduction in prices and relative income in Figure 2.

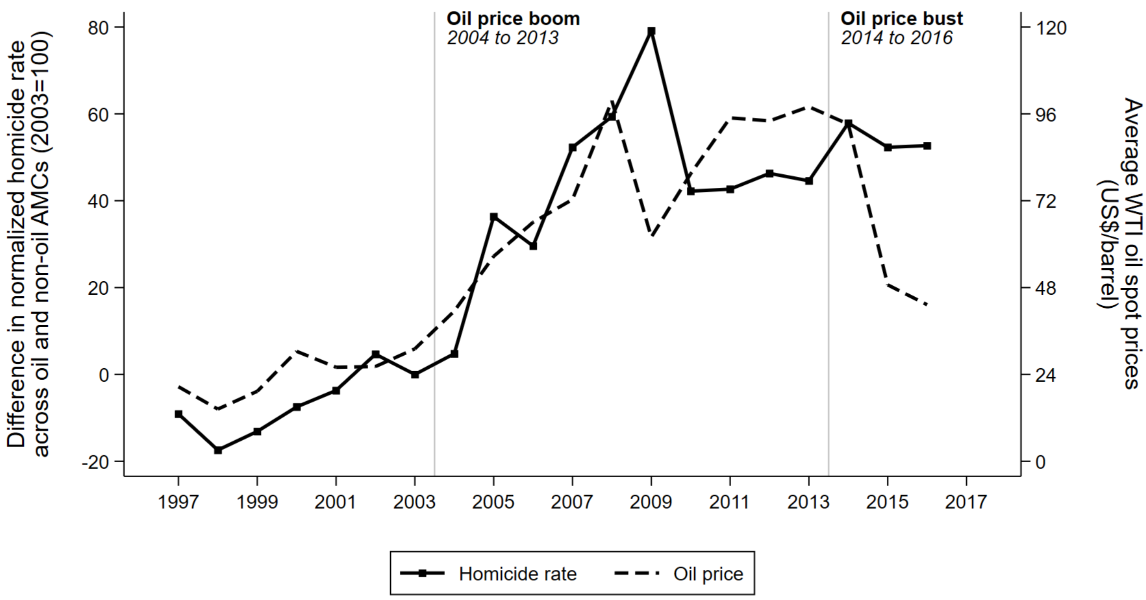

FIGURE 3: HOMICIDE RATE AND OIL PRICES

Together, Figures 2 and 3 seem puzzling. Given the tightly controlled and heavily regulated Brazilian oil market, a positive income shock should lead to higher wages and increased legal labor market opportunities, increasing the opportunity cost of crime. In reality, Cavalcanti, da Mata and Toscani (2019) document that the oil boom indeed led to increases in employment in both manufacturing and services, and to increases in the incidence of high value-added activities, indicating, for all practical purposes, positive impacts on local economic development. In addition, the rapacity effect highlighted by Dube and Vargas (2013) do not seem like an appealing explanation in our setting. Oil production in Brazil occurs mostly in offshore wells controlled by a small set of large firms, particularly the state-owned giant *Petrobras*. These market characteristics do not leave much room for an increase in violence from a direct dispute over oil production and distribution. In the next sections, we analyze this evidence formally and explore potential explanations for this puzzle.

4 Empirical Strategy

We use the local presence of an oil well that produced at any point in time to define AMCs directly impacted by the oil boom. By looking at wells that were active at any point in time rather than to production directly, we hope to minimize potential endogeneity problems associated with the decision to produce at a certain moment. Production decisions may be affected by time-varying local infrastructure and access to markets, which may also be correlated with other determinants of crime.

To assess the effect of the oil boom on crime and other local outcomes, we rely primarily on the following difference-in-differences specification:

$$\begin{aligned} Y_{it} = \beta_0 + &\beta_1 \cdot (Well_i \times D_{2004 \leq t \leq 2013}) \\ &\beta_2 \cdot (Well_i \times D_{2014 \leq t \leq 2016}) + X_{it}'\phi + \theta_i + \lambda_{st} + \epsilon_{it}, \end{aligned} \tag{1}$$

where Y_{it} is the outcome variable for AMC i in year t; $Well_i$ is a dummy variable indicating the presence of an ever-producing oil well in AMC i; $D_{2004 \leq t \leq 2013}$ and $D_{2014 \leq t \leq 2016}$ are dummy variables indicating, respectively, the oil boom and bust periods; X_{it} is a vector of baseline covariates interacted with year dummies, which allows us to control for predetermined characteristics that may be correlated with the evolution of the dependent variable over time; θ_i indicates AMC fixed effects; λ_{st} represents state-year fixed effects that control for state-level common trends; and ϵ_{it} is a random error term. Standard errors are clustered at the AMC level.

The X_{it} vector includes the log of population, the log of average household income per capita, the share of urban population, the fraction of individuals below the poverty line, income inequality measured by the Gini coefficient, the fraction of individuals between ages 20 and 39, average years of schooling, the share of employment in the manufacturing sector, and the share of employment in the oil sector, all calculated from the 2000 census and interacted with year dummies. We include these controls in our specification to account for potential differences in the evolution of income and violence that are driven by socioeconomic and demographic heterogeneity across oil and non-oil areas.

Since our definition of the boom and bust periods may be seen as somewhat arbitrary, we also estimate two-way fixed effects models where the treatment variable is defined as the interaction of the oil presence dummy ($Well_i$) with the lagged value of the log of the international price of oil ($log(P_{t-1})$). This strategy considers the international price of oil as a source of exogenous variation in local incomes, similarly to Acemoglu, Finkelstein and Notowidigdo (2013) and Dube and Vargas (2013). Ideally, we would like to interact the spot oil price with local oil reserves in order to measure the potential value of the oil market in each local economy. However, data on oil reserves at the AMC level are not available. So, instead, we interact the WTI spot oil price with our $Well_i$ dummy. This specification also allows for an interpretation based on the marginal effect of proportional changes in oil prices on local outcomes. It is estimated using the following equation:

$$Y_{it} = \delta_0 + \delta_1 \cdot (log(P_{t-1}) \times Well_i) + X_{it}^{'}\phi + \theta_i + \lambda_{st} + \epsilon_{it}, \tag{2}$$

where P_{t-1} is the WTI oil price in $t-1$, and $Well_i$, X_{it}, θ_i, λ_{st} are defined as before. By considering the lagged oil price instead of its contemporaneous value we are assuming that shocks to international markets take time to translate into sizeable impacts on income in local economies. We show in the appendix that our main results remain unchanged when we use $log(P_t)$ instead of $log(P_{t-1})$. As before, standard errors are clustered at the AMC level.

When estimating the models described above, we assume that oil and non-oil AMCs would display similar trajectories were it not for the oil boom in the first specification, or for movements in the international price of oil in the second one. We provide evidence on the validity of this parallel trends assumption for the first specification by estimating an analogous version of equation (1) in an event-study framework.

Still, oil and non-oil AMCs are different in many observable dimensions, as can be seen in Table 1. To deal with the potential problems raised by such heterogeneity, we use a propensity score estimator to re-weight AMCs in equations (1) and (2). First, we use a probit model to estimate the probability $\hat{p}$ that each AMC has an oil well—or, in other words, is in the treatment group—as a function of a number of characteristics calculated from the 2000 population census. We use the same variables included in the vector X_{it}

as regressors in the probit model: log of population, log of average household income per capita, share of urban population, share of individuals below the poverty line, Gini coefficient, share of individuals between ages 20 and 39, average years of schooling, share of individuals working in the manufacturing sector, and share of individuals working in the oil sector. For the interested reader, the results of our propensity score equation are presented in Appendix Table A.1.

Then, following Hirano, Imbens and Ridder (2003) and Busso, DiNardo and McCrary (2014), we use the estimated propensity score $\hat{p}$ to reweight each treated AMC by $1/\hat{p}$ and each non-treated AMC by $1/(1-\hat{p})$, as Linnemayr and Alderman (2011) and Guadalupe, Kuzmina and Thomas (2012). We also drop from the analysis AMCs with $\hat{p}$ below 5% and above 95%, to avoid extreme outliers in our weights. Table 2 shows the balance test on observables before and after the re-weighting procedure. After the propensity score weighting, differences across treatment and control become very small and statistically non-significant. Appendix Figure A.2 plots the distributions of the estimated propensity scores for treated and non-treated AMCs, before and after the matching. The Appendix also presents results for all our specifications without propensity score weighting (simple diff-in-diff and two-way fixed-effects models). The qualitative patterns of our key results remain all the same without the weighting procedure.

In the next section, we start by documenting the impact of the oil boom on local incomes, employment, and violence. These exercises build upon the descriptive evidence from Figures 2 and 3 and give them a causal interpretation. We also provide evidence on the absence of pre-trends for these two key results. Following, we explore various potential channels linking the increases in local income to crime, including density, urbanization, illegal markets, provision of public goods, and relative labor and capital earnings.

5 Main results

5.1 Homicides and Income

Table 3 reports estimates for β_1 and β_2 from equation (1) in panel A and for δ_1 from equation (2) in panel B. The first three columns in the table present results for the homicide rate, while the last three display the results for GDP per capita. Columns (1) and (4) include only AMC and year fixed effects, whereas all remaining columns include state-year fixed effects. Columns (3) and (6), in addition, include the interaction of baseline (2000) characteristics with year dummies. In all columns, treated and control AMCs are weighted by $1/\hat{p}$ and $1/(1-\hat{p})$, respectively.

The first three columns of panel A suggest that oil regions experienced a relative

TABLE 2: PROPENSITY-SCORE MATCHING BALANCE TEST

	Unmatched			Matched		
Dependent variables	Treated (1)	Control (2)	Difference (3)	Treated (4)	Control (5)	Difference (6)
Log of population	10.936	9.824	1.112***	10.895	10.905	−0.010
			[0.337]			[0.240]
Log of household income per capita	6.624	6.708	−0.084	6.529	6.617	−0.088
			[0.075]			[0.066]
Share of urban population	0.786	0.794	−0.009	0.744	0.768	−0.024
			[0.043]			[0.040]
Share of individuals below the poverty line	0.243	0.166	0.077***	0.278	0.254	0.024
			[0.022]			[0.022]
Gini coefficient	0.567	0.526	0.040***	0.578	0.571	0.007
			[0.013]			[0.008]
Share of individuals 20-39 years old	0.328	0.322	0.006	0.324	0.327	−0.002
			[0.005]			[0.004]
Average years of schooling	4.524	4.792	−0.268*	4.296	4.506	−0.210
			[0.157]			[0.144]
Share of employed in the manuf. sector	0.085	0.148	−0.063***	0.090	0.081	0.009
			[0.022]			[0.009]
Share of employed in the oil sector	0.005	0.001	0.004***	0.002	0.005	−0.002
			[0.001]			[0.003]

Notes: Columns (1) and (2) show the mean of each variable conditional on the treatment status. Columns (4) and (5) show the reweighted means in which each treated AMC is weighted by $1/\hat{p}$ and each non-treated AMC by $1/(1-\hat{p})$. Column (3) shows the estimated coefficient of an OLS regression in which an indicator variable for treatment status is the independent variable. In column (6) we do the same regressions of column (3) but using the propensity score weights. Standard errors are reported in brackets in columns (3) and (6). Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $***$.

increase in homicides during both the oil boom and bust periods. There is a reduction in the magnitude of the estimated coefficients once we include state-year fixed effects and move from column (1) to column (2), but virtually no additional change as we introduce additional controls in column (3). This suggests that differential trends across locations with distinct initial conditions are probably not a concern in our specification. The coefficient in column (3) represents a relative increase of roughly 10 homicides per $100,000$ inhabitants in oil AMCs during the boom period. The relative increase in homicide rates grows during the bust period, suggesting that the effect from the boom years persisted over time. This latter result is also due to the fact that differences in homicide rates are still very small during the first years of the boom, while the bust period starts already with very high levels. So, the average differential for the boom period is overall smaller than that for the bust (see the dynamic pattern in Figure 3, for example).

Similarly, the results from panel B suggest that, as the price of oil increased during our sample period, so did homicides in AMCs with the presence of oil wells, when compared to AMCs without wells. The qualitative pattern of the results across columns follows that from panel A. The quantitative implications from this specification are also in line with those discussed before: a 100% increase in oil prices, not too distant from the rise in prices observed during the boom, is associated with a relative increase of 9.9 homicides per $100,000$ inhabitants in oil AMCs.

The last three columns in Table 3 suggest that, as a response to increases in international oil prices, oil AMCs experienced a relative increase in GDP per capita. In both panels A and B, coefficients increase as we move from columns (1) to (3). GDP per capita in oil AMCs experienced relative increases of, on average, 0.344 log points during the boom period, and 0.575 during the bust (compared to the pre-boom levels). The same statistical "illusion" discussed in the case of homicides applies here as well. As Figure 2 shows, there is a relative reduction in GDP per capita during the bust period. But, since the bust period starts with very high GDP levels, when we calculate average effects in the regressions in Table 3, the average for the bust ends up being higher than that for the boom. Therefore the larger coefficient that appears to contradict the definitions of boom and bust.[3]

In Tables 4 and 5, we go one step further and try to shed light on the nature of the increases in violence and income documented in Table 3. From now on, for the sake of brevity, we present only results from our most complete specification, including state-year fixed effects and interactions of baseline characteristics and time dummies.

Table 4 shows the breakdown of our previous results by different types of homicides and victims' characteristics (the denominator of the dependent variable remains the same across columns, so coefficients can be directly compared across them). The relative increase in violence seems to be concentrated almost entirely on young males and homicides caused by firearms occurring outside of the vitims' home. Specifically, 100% of the estimated effect comes from male homicides, 80% among ages 15 and 39, and, among those, all occurring outside of the victims' home, 88% by firearm, and 86% involving single individuals. The pattern suggests that it is unlikely that interpersonal violence associated with domestic disputes is behind the results. For the interested reader, Appendix Tables A.6 and A.7 present additional results on homicides by specific location of occurrence and type of aggression.

The breakdown of the income result is presented in Table 5. Given the importance of the oil industry itself, the relative increase in GDP seems to be concentrated in the

[3]Appendix Table A.3 presents unweighted results using the same specifications from Table 3. Qualitative conclusions remain unchanged under the simple difference-in-differences and two-way fixed-effects models that ignore the propensity score weighting. The qualitative results from Tables 4 and 5 also remain unchanged when we use the unweighted specification. See Appendix Tables A.4 and A.5.

TABLE 3: HOMICIDES AND INCOME DURING THE OIL BOOM AND BUST PERIODS

	Homicides per 100,000 inhabitants			Log of GDP *per capita*		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Boom and bust treatment						
well × boom period	14.131***	10.105***	9.836***	0.256*	0.304**	0.344**
	[3.097]	[2.767]	[2.553]	[0.153]	[0.133]	[0.136]
well × bust period	18.277***	14.760***	15.576***	0.268	0.487*	0.575**
	[5.254]	[4.219]	[3.112]	[0.339]	[0.269]	[0.280]
Panel B: Lagged oil price treatment						
well × log(lagged oil price)	13.236***	9.953***	9.971***	0.242	0.328**	0.376**
	[2.789]	[2.305]	[1.924]	[0.179]	[0.142]	[0.153]
State × Year FE		X	X		X	X
Baseline charact. × Year FE			X			X
Dep. variable mean	29.88	29.88	29.88	10.13	10.13	10.13
Observations	1,840	1,840	1,840	1,656	1,656	1,656

Notes: In brackets, standard errors are clustered at the AMC level. The sample includes AMCs from Brazil's coastal states of *São Paulo*, *Rio de Janeiro*, and *Espírito Santo*. All regressions are weighted by a function of the propensity score estimate $\hat{p}$. We include AMC fixed effects in all regressions and year fixed effects alone in columns (1) and (4). The baseline characteristics in columns (3) and (6) come from the 2000 Population Census and include the log of AMC's population, the lof of average household income per capita, the share of urban population, the fraction of individuals below the poverty line, Gini coefficient, the fraction of individuals in the 20-39 years old interval, average years of schooling, the share of formal employment in the manufacturing sector, and the share of formal employment in the oil sector. Due to data availability, columns (4)-(6) regression sample starts in 1999 while columns (1)-(3) uses data from the whole 1997-2016 period. Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $***$.

manufacturing sector. The share of the manufacturing sector in GDP in oil AMCs increases 16 percentage points during the boom period. Despite no effect on agriculture, the boom had positive spillovers on services, which could be the result of increased demand in a fast-growing economy. Finally, the last two columns explore employment and earnings data from the Brazilian Ministry of Labor's RAIS dataset. Despite the noisy estimates, the results suggest that there were substantial increases in formal employment and earnings in oil areas during the period. Panel B, for example, suggests elasticities of 0.08 and 0.06 of employment and earnings, respectively, in relation to international oil prices. Appendix Table A.8 presents sectoral results using the RAIS data and documents significant expansions in employment in mining, construction, financial institutions, food and hotel, and public administration. The results related to income, employment, and

TABLE 4: HOMICIDES DECOMPOSITION BY LOCATION, WEAPON USED, AND VICTIMS CHARACTERISTICS

	Homicides			Male homicides		Male homicides, ages 15-39		
	All	Firearm	Outside of home	All ages	Ages 15-39	Single	Outside home	Firearm
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Boom and bust treatment								
well × boom period	9.836***	8.691***	9.307***	9.858***	7.852***	6.760***	7.742***	6.925***
	[2.553]	[1.735]	[2.509]	[2.335]	[1.661]	[1.345]	[1.675]	[1.343]
well × bust period	15.576***	15.358***	12.642***	14.381***	11.055***	9.535***	9.522***	11.490***
	[3.112]	[3.351]	[2.617]	[2.847]	[2.453]	[2.057]	[1.988]	[2.621]
Panel B: Lagged oil price treatment								
well × log(lagged oil price)	9.971***	8.308***	8.455***	9.693***	7.437***	6.742***	6.648***	6.432***
	[1.924]	[1.675]	[1.767]	[1.661]	[1.339]	[1.164]	[1.232]	[1.335]
Observations	1,840	1,840	1,840	1,840	1,840	1,840	1,840	1,840

Notes: In brackets, standard errors are clustered at the AMC level. The sample includes AMCs from Brazil's coastal states of *São Paulo*, *Rio de Janeiro*, and *Espírito Santo*. All regressions are weighted by a function of the propensity score estimate $\hat{p}$. We include AMC fixed effects, state-year fixed effects, and the following controls, measured in the 2000 Population Census and interacted with a full set of year dummies, in all regressions: the log of AMC's population, the log of average household income per capita, the share of urban population, the fraction of individuals below the poverty line, Gini coefficient, the fraction of individuals in the 20-39 years old interval, average years of schooling, the share of formal employment in the manufacturing sector, and the share of formal employment in the oil sector. Regression samples in all columns use data from the whole 1997-2016 period. Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $***$.

sectoral composition reproduce, to a large extent, those obtained before by Cavalcanti, da Mata and Toscani (2019). These authors show that, in addition, the oil boom shifted the productive structure of affected areas to higher-value-added activities.

5.2 Dynamic Effects

Even with the propensity score matching and controlling for local characteristics interacted with time dummies and state-level common trends, the causal interpretation of difference-in-differences models relies on the validity of the parallel trends assumption. We provide evidence that parallel trends hold in our setting by using an event-study framework, which also allows us to assess the dynamic effects during the oil boom and bust periods in a more flexible and agnostic way. Formally, we estimate the following regression:

$$Y_{it} = \alpha_0 + \alpha_t \times Well_i \times Year_t + X_{it}^{'}\phi + \theta_i + \lambda_{st} + \epsilon_{it}, \tag{3}$$

TABLE 5: INCOME SPILLOVER EFFECTS AND FORMAL LABOR MARKET OUTCOMES

			Log of sectoral GDP			GDP shares			Employment and earnings	
	Log of GDP	Log of GDP *per cap*	Agriculture	Manuf.	Services	Agriculture	Manuf.	Services	Log of employment	Log of earnings
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Boom and bust treatment										
well × boom period	0.393***	0.344**	−0.037	0.948***	0.245**	−0.042***	0.160***	−0.051***	0.111	0.086*
	[0.133]	[0.136]	[0.069]	[0.228]	[0.123]	[0.014]	[0.033]	[0.013]	[0.075]	[0.049]
well × bust period	0.650**	0.575**	−0.006	1.353***	0.465**	−0.039*	0.194***	−0.078**	0.140	0.131
	[0.272]	[0.280]	[0.107]	[0.480]	[0.223]	[0.021]	[0.066]	[0.030]	[0.085]	[0.089]
Panel B: Lagged oil price treatment										
well × log(lagged oil price)	0.422***	0.376**	−0.017	0.894***	0.294**	−0.032**	0.143***	−0.048***	0.081	0.066
	[0.149]	[0.153]	[0.063]	[0.236]	[0.127]	[0.013]	[0.033]	[0.014]	[0.062]	[0.050]
Observations	1,656	1,656	1,656	1,656	1,656	1,656	1,656	1,656	1,840	1,840

Notes: In brackets, standard errors are clustered at the AMC level. The sample includes AMCs from Brazil's coastal states of *São Paulo*, *Rio de Janeiro*, and *Espírito Santo*. All regressions are weighted by a function of the propensity score estimate $\hat{p}$. We include AMC fixed effects, state-year fixed effects, and the following controls, measured in the 2000 Population Census and interacted with a full set of year dummies, in all regressions: the log of AMC's population, the log of average household income per capita, the share of urban population, the fraction of individuals below the poverty line, Gini coefficient, the fraction of individuals in the 20-39 years old interval, average years of schooling, the share of formal employment in the manufacturing sector, and the share of formal employment in the oil sector. Due to data availability, columns (1)-(8) regression sample starts in 1999 while columns (9)-(10) uses data from the whole 1997-2016 period. Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $***$.

where $Year_t$ is a dummy variable equal to 1 for year t and all other variables are defined as before. The $Year_t$ variable for 2003 is omitted, so that the first pre-boom year is the reference point in the event-study analysis. The year-specific coefficients α_t in this specification capture the relative deviation across oil and non-oil AMCs for each calendar year in the sample, when compared to the differences observed in the reference year 2003. Again, observations are weighted by a function of the propensity score estimate $\hat{p}$.

Figure 4 presents the estimated coefficients graphically, together with the respective 90% cluster-robust confidence intervals. Panels A and B suggest that before 2004, the year in which the oil boom started, both the homicide rate and GDP per capita displayed similar trajectories across oil and non-oil AMCs, providing support to the validity of the parallel trends assumption. Once the international oil price started increasing, these trends decoupled. As in columns (3) and (6) of Table 3, both the homicide rate and GDP per capita grew substantially faster in oil AMCs during the boom period (2004-2013). The point estimates for GDP per capita track closely the oil price decline also during the bust period after 2014. For homicides rates, point estimates follow closely the trajectory of oil prices during the boom period, but remain positive and stable when oil prices collapse during the bust. The figures reproduce the descriptive patterns documented before in Figures 2 and 3, but now in a regression setting in which we use propensity score weighting and account for the possibility of differential trends across states and AMCs with distinct initial conditions.[4]

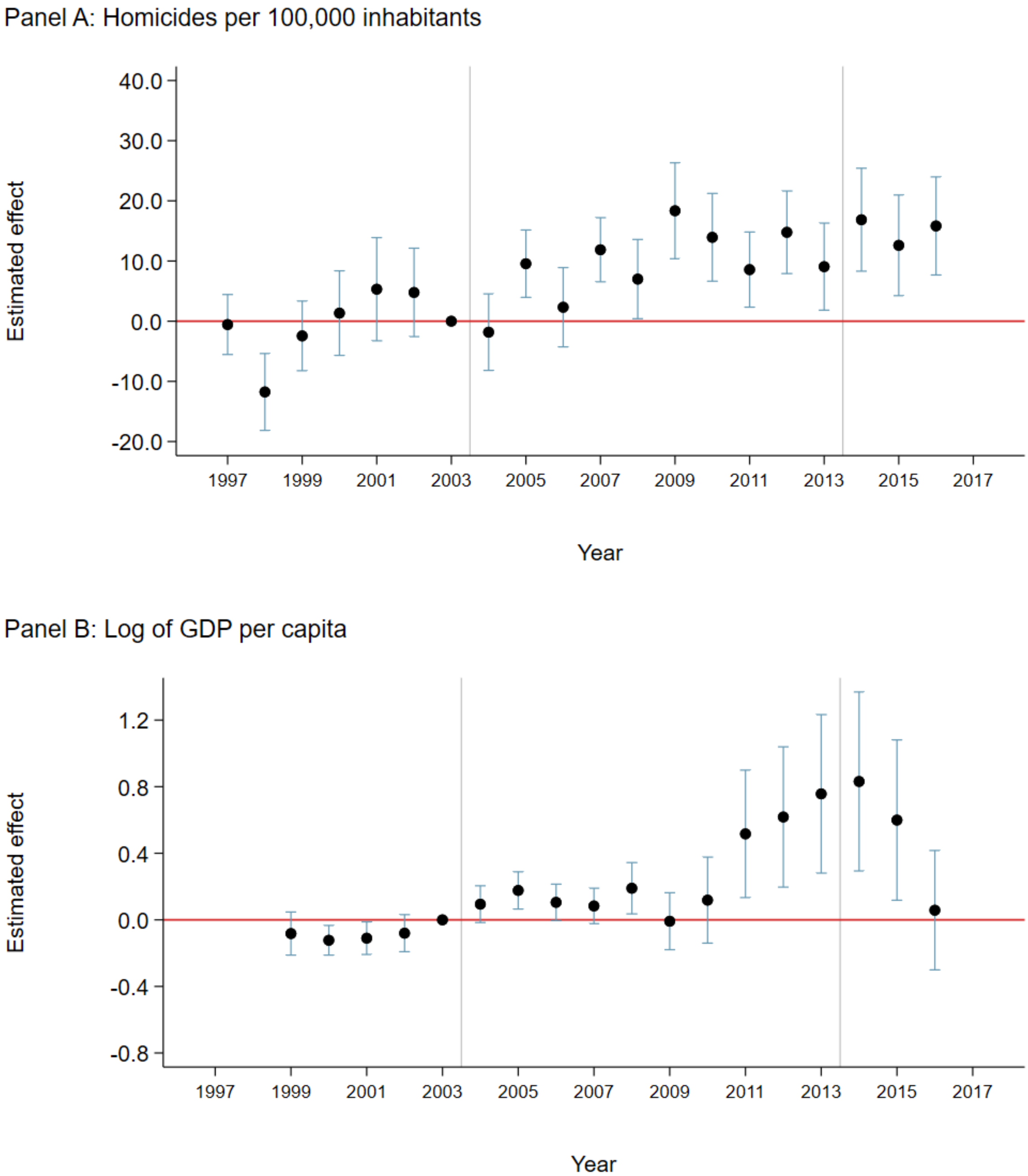

FIGURE 4: DYNAMIC EFFECTS ON HOMICIDES AND GDP

[4]Figure A.3 shows the event study results for homicides and income decompositions.

5.3 Mechanisms

In this section, we explore potential mechanisms behind the puzzling increase in crime in oil-producing regions during the boom period. Since the income shock was driven by a capital-intensive sector, relative labor market conditions may be negatively affected (when compared to capital returns), leading to increases in crime as a general equilibrium effect, as suggested by Dal-Bó and Dal-Bó (2011). Also, accelerated growth can lead to indirect effects on crime and violence through its impacts on density, urbanization, demand for illegal goods, and provision of public goods, as discussed in detail by Ferraz, Soares and Vargas (2022). If the combination of these changes in relative prices and indirect effects is stronger than the direct impact on improved wages and employment, it is possible that the relative return to crime actually goes up with the positive income shock, even when it is from a legal source.

Table 6 explores potential general equilibrium effects from changes in the income distribution and population composition. Columns (1) to (5) show that, in all dimensions considered, there were increases in inequality. Columns (1) and (2) document persistent increases in wage inequality, as measured by the ratio between the top 10% and bottom 10% of wages and the Gini coefficient. In columns (3), (4), and (5) of Table 6, we present evidence that this increase inequality is also present when we look at returns to capital and labor, and also to skilled and unskilled labor. First, there is a negative and significant effect on the ratio between total formal payroll and local GDP, with a cumulative decrease of 0.002 log points in oil AMCs, when compared to non-oil AMCs. This suggests a relative increase in the share of capital in local income. Second, there are increases in both the wage ratio between college and high-school workers and between white-collar and blue-collar workers, specially during the boom period. These patterns give support to the mechanism proposed by Dal-Bó and Dal-Bó (2011): a positive shock to the price of a capital-intensive good should increase relatively more the returns to capital, and also to its complementary factors (skilled labor). Finally, columns (6) and (7) suggest that there were no significant changes in the composition of formal employment in these regions.

But these general equilibrium effects are not the only potential indirect mechanisms linking local income shocks to crime. Table 7 explores two additional channels: urbanization and illegal markets. As proxies for urbanization, we consider population density, AMC area covered with urban infrastructure, and mortality due to traffic accidents (we see mortality due to traffic accidents as a measure of urban population and mobility). Column (1) shows that there were relative increases in density during both the oil boom and bust periods, with a cumulative relative increase of 0.093 log points in oil AMCs, when compared to non-oil AMCs. Estimates in column (2) show a relative increase in the

TABLE 6: EFFECTS ON INCOME DISTRIBUTION AND POPULATION COMPOSITION

	Inequality		Skilled and unskilled labor rents			Population composition	
	Wage ratio between top 10% and bottom 10%	Wage Gini	Log of the ratio between RAIS earnings and local GDP	Log of the ratio between college and highschool workers' wage	Log of the ratio between white collar and blue collar workers' wage	Ratio between the # of men and women labor contracts	Average age of formal employed men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Boom and bust treatment							
well × boom period	0.752**	0.013**	−0.001***	0.060	0.048	0.037	0.014
	[0.323]	[0.006]	[0.000]	[0.078]	[0.032]	[0.063]	[0.181]
well × bust period	1.083**	0.022**	−0.002***	−0.037	0.047	−0.082	−0.171
	[0.440]	[0.008]	[0.001]	[0.078]	[0.029]	[0.082]	[0.289]
Panel B: Lagged oil price treatment							
well × log(lagged oil price)	0.609**	0.011**	−0.001***	0.012	0.033*	−0.033	−0.019
	[0.279]	[0.005]	[0.000]	[0.057]	[0.020]	[0.057]	[0.164]
Observations	1,748	1,748	1,656	1,748	1,748	1,748	1,748

Notes: In brackets, standard errors are clustered at the AMC level. The sample includes AMCs from Brazil's coastal states of *São Paulo*, *Rio de Janeiro*, and *Espírito Santo*. All regressions are weighted by a function of the propensity score estimate $\hat{p}$. We include AMC fixed effects, state-year fixed effects, and the following controls, measured in the 2000 Population Census and interacted with a full set of year dummies, in all regressions: the log of AMC's population, the log of average household income per capita, the share of urban population, the fraction of individuals below the poverty line, Gini coefficient, the fraction of individuals in the 20-39 years old interval, average years of schooling, the share of formal employment in the manufacturing sector, and the share of formal employment in the oil sector. Due to data availability, column (3) regression sample starts in 1999 while all other columns uses data from the 1998-2016 period. Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $***$.

area covered with urban infrastructure, reaching 0.168 log points in the later period. The point estimates in column (3), in turn, suggest relative increases in deaths due to traffic accidents, though the estimates are not statistically significant. Together, these first three columns indicate an increase in urbanization driven by the oil boom, potentially bringing with it the typical problems of urban areas.

Our results on population density may be regarded with suspicion, since local population data from IBGE for inter-census years are imputed based on demographic models. For this reason, Table A.10 replicates our results on population density from column (1)—as well as all other estimations in the paper that rely on population data—using WorldPop data instead. WorldPop is a recent database that estimates local population in inter-census years for various countries using initial and final date information from censuses and satellite images and machine-learning techniques for inter-census years. Unfortunately, WorldPop's population data starts in 2000, which makes it better suited for robustness checks than as our primary population measure. Our results are virtually identical when we use this alternative population variable in the 2000-2016 period.

Columns (4) to (7) in Table 7 consider different proxies for illegal market activity: deaths due to overdose, drugs and firearms seizures, and the fraction of suicides by firearms.[5] The first two variables proxy for activity in the illegal drugs market, while the last two assess local availability of firearms, which may be seen as an indirect evidence of increased activities in illegal markets in general. The table shows a positive and significant effect on deaths by drug overdose during both the boom and bust periods. There is also a positive effect on the fraction of suicides by firearms and drug seizures after 2013. The coefficients for drug and firearm seizures, however, must be interpreted with caution, given the reduced time interval and number of observations. So, overall, there seems to be some evidence of increased activity in the illegal drugs market. [6]

TABLE 7: EFFECTS ON URBANIZATION AND ILLEGAL MARKETS ACTIVITY

	Urbanization			Illegal markets			
	Log of pop. density	Log of area covered with urban infrastructure	Traffic accident deaths per 100,000 inhab.	Drug overdose deaths per 100,000 inhab.	Drug seizures per 100,000 inhab.	Firearm seizures per 100,000 inhab.	Fraction of suicides by firearm
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Boom and bust treatment							
well × boom period	0.068***	0.110**	0.214	0.295***	15.162	−8.783	0.014
	[0.017]	[0.046]	[1.409]	[0.093]	[12.189]	[23.100]	[0.029]
well × bust period	0.093***	0.168**	2.728	0.639***	27.745*	−3.983	0.104**
	[0.027]	[0.077]	[2.015]	[0.151]	[14.896]	[36.264]	[0.045]
Panel B: Lagged oil price treatment							
well × log(lagged oil price)	0.059***	0.098**	0.628	0.353***	23.858***	−33.801	0.039*
	[0.016]	[0.045]	[1.065]	[0.075]	[8.472]	[27.036]	[0.024]
Observations	1,840	1,840	1,840	1,840	938	938	1,840

Notes: In brackets, standard errors are clustered at the AMC level. The sample includes AMCs from Brazil's coastal states of *São Paulo*, *Rio de Janeiro*, and *Espírito Santo*, except for columns (5)-(6) which do not include data for *Espírito Santo*. All regressions are weighted by a function of the propensity score estimate $\hat{p}$. We include AMC fixed effects, state-year fixed effects, and the following controls, measured in the 2000 Population Census and interacted with a full set of year dummies, in all regressions: the log of AMC's population, the log of average household income per capita, the share of urban population, the fraction of individuals below the poverty line, Gini coefficient, the fraction of individuals in the 20-39 years old interval, average years of schooling, the share of formal employment in the manufacturing sector, and the share of formal employment in the oil sector. Due to data availability, columns (5)-(6) regression sample starts in 2003 while all other columns uses data from the whole 1997-2016 period. Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $***$.

At last, Table 8 shifts attention to public good provision. We look at overall govern-

[5]From 2003 to 2016, we have data for firearms and drugs seizures only for the states of Rio de Janeiro and São Paulo. The fraction of suicides by firearms, in turn, is a traditional proxy for the local availability of firearms and is available for the entire sample.

[6]For the interested reader, Figure A.4 presents the event-study graphs for all the dependent variables analyzed in Tables 6 and 7. Results for the log of population density may seem awkward for the years of 1997, 1998 and 1999, but this is due to the fact that the estimated population data apparently was not updated—at least for some small/medium-sized municipalities—after the publication of the 2000 Demographic Census.

ment expenditure, revenue, and proxies for the provision of public health and education. Rather than claiming that each of these dimensions may individually contribute to the observed increase in crime, the objective of this table is to explore how public good provision, along various dimensions, responded to the observed increases in income, population, and urbanization. Columns (1)-(6) from panels A and B show positive effects on the log of public expenditures and revenues, of very similar magnitude, suggesting that the relative increase in oil production and economic activity had a significant effect on local public finance. Despite the also large effect on both the log of public expenditures and revenues *per capita*, point estimates are statistically significant only during the bust period. Finally, columns (5) and (6) show that the share of royalties in local revenues and expenditures increased during the period.

In terms of public health provision, point estimates in Table 8 suggest a relative reduction in both the number of beds per $100,000$ inhabitants and the number of family health teams (*Equipes Saúde da Família*, ESF), though the results are not statistically significant. The Brazilian Family Health Program, which experienced significant expansions during our sample period, is widely regarded by the international public health community as a very successful intervention, with positive impacts on access and health outcomes (see, for example, Bhalotra, Rocha and Soares (2019)).

Finally, regarding schooling, point estimates for net enrollment rates are always negative. Despite being non-significant for primary education, Table 8 shows a relative reduction during the boom period of 1.2 percentage points in the secondary enrollment rate. There is also evidence of a marginally statistically significant negative effect on the number of teachers per student in secondary education. Though we see an increase of 0.4 teachers per 100 students in primary education during boom years, secondary education lost roughly 1 teacher per 100 students during the bust.

Taken together, the results from Table 8 suggest no clear benefit from the oil shock on the provision of local public goods.[7] Despite the royalties received by oil-producing municipalities and increased local economic activity, in most cases expenditures seem to have only been able to, at best, keep up with population growth.[8] In most cases, point estimates are actually negative, indicating a deterioration in public good provision per capita. There is also an indication of significant deterioration along specific dimensions,

[7]Event-study results for all the outcomes of Table 8 also suggest no clear effect on public good provision over the years. See Figure A.5.

[8]In Appendix Table A.9, we show that despite a still positive and significant effect on local GDP and GDP per capita net of royalties, the effect on the level of overall expenditures, expenditures per capita, and revenues per capita is not significant anymore when we subtract royalties. Point estimates on expenditures per capita net of royalties, in particular, even become negative.

TABLE 8: EFFECTS OF ACCELERATED GROWTH AND FISCAL WINDFALLS ON PUBLIC GOOD PROVISION

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Public finance						Health		
	Log of public expenditures	Log of public expenditures *per cap.*	Log of public revenues	Log of public revenues *per cap.*	Royalties revenues as % of public expenditures	Royalties revenues as % of public revenues	Hospital presence (beds)	# of beds per 100,000 inhab.	ESF per 100,000 inhab.
Panel A: Boom and bust treatment									
well × boom period	0.146**	0.087	0.165**	0.106	0.075**	0.036**	−0.012	−19.278	−1.191
	[0.064]	[0.065]	[0.068]	[0.068]	[0.033]	[0.018]	[0.023]	[27.399]	[1.318]
well × bust period	0.376**	0.295*	0.369**	0.289*	0.126**	0.081**	0.020	−11.890	−1.622
	[0.154]	[0.161]	[0.146]	[0.153]	[0.061]	[0.041]	[0.018]	[33.888]	[2.308]
Panel B: Lagged oil price treatment									
well × log(lagged oil price)	0.150*	0.098	0.171**	0.120	0.075*	0.045**	0.005	−17.445	−0.800
	[0.078]	[0.082]	[0.081]	[0.085]	[0.038]	[0.021]	[0.015]	[19.896]	[1.262]
Observations	1,731	1,731	1,730	1,730	1,731	1,730	1,748	1,748	1,748
	Primary education			Secondary education					
	Schools per students	Teachers per students	Net enrollment rate	Schools per students	Teachers per students	Net enrollment rate			
Panel C: Boom and bust treatment									
well × boom period	0.000	0.004**	−0.010	0.003	−0.001	−0.012***			
	[0.000]	[0.002]	[0.017]	[0.003]	[0.004]	[0.004]			
well × bust period	0.000	0.007	−0.008	0.003	−0.009*	−0.008			
	[0.001]	[0.004]	[0.015]	[0.003]	[0.005]	[0.010]			
Panel D: Lagged oil price treatment									
well × log(lagged oil price)	0.000	0.004*	−0.007	0.003	−0.003	−0.011**			
	[0.000]	[0.002]	[0.013]	[0.002]	[0.003]	[0.004]			
Observations	1,840	1,840	1,748	1,840	1,840	1,748			

Notes: In brackets, standard errors are clustered at the AMC level. The sample includes AMCs from Brazil's coastal states of *São Paulo*, *Rio de Janeiro*, and *Espírito Santo*. All regressions are weighted by a function of the propensity score estimate $\hat{p}$. We include AMC fixed effects, state-year fixed effects, and the following controls, measured in the 2000 Population Census and interacted with a full set of year dummies, in all regressions: the log of AMC's population, the log of average household income per capita, the share of urban population, the fraction of individuals below the poverty line, Gini coefficient, the fraction of individuals in the 20-39 years old interval, average years of schooling, the share of formal employment in the manufacturing sector, and the share of formal employment in the oil sector. Due to data availability, columns (7)-(8) uses data from 1997-2015 period, column (9) and also columns (3) and (6) from panels C and D uses data from 1998-2016, all other regressions uses data from the whole 1997-2016 period. Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $***$.

such as secondary enrollment. Together with the evidence on the expansion of public employment, discussed before and documented in Appendix Table A.8, the results presented here tend to confirm the findings of Monteiro and Ferraz (2010). Most of the additional income received by oil AMCs seems to have translated into increased public employment, without clear improvements in the overall provision of public goods.

Bringing together the results from Tables 6, 7, and 8, we can paint an overall picture of the changes happening in oil-producing locations that is remarkably consistent with the observed increase in crime. The combination of increasing inequality, accelerated urbanization, and increased presence of illegal drugs, in a context of sluggish responses in the provision of public goods, seems key to rationalize the documented patterns.

6 Concluding Remarks

We show that oil-producing areas of Brazil experienced increases in crime during the oil boom of the 2000s, at the same time as local economic activity grew. Exploring various different data sources, we show that, during this period, these areas also experienced increasing inequality and accelerated expansions in density and urbanization, coupled with increased presence of illegal drugs, but without concomitant improvements in public good provision.

These results point to subtleties in the relationship between local economic shocks and crime that have not been fully appreciated by the previous empirical literature. As suggested by Ferraz, Soares and Vargas (2022), besides the nature of the economic shock—whether legal or illegal—, it is important as well to understand its broader implications to the local socioeconomic landscape, including equilibrium impacts on the distribution of income, density, anonymity, demand for illegal goods, and state presence. Our results show that these considerations are not mere theoretical curiosities, but can indeed be important, particularly when shocks are sufficiently large and disruptive. Wealthier does not always mean safer.

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Online Appendix (NOT FOR PUBLICATION)

A Additional Tables and Figures

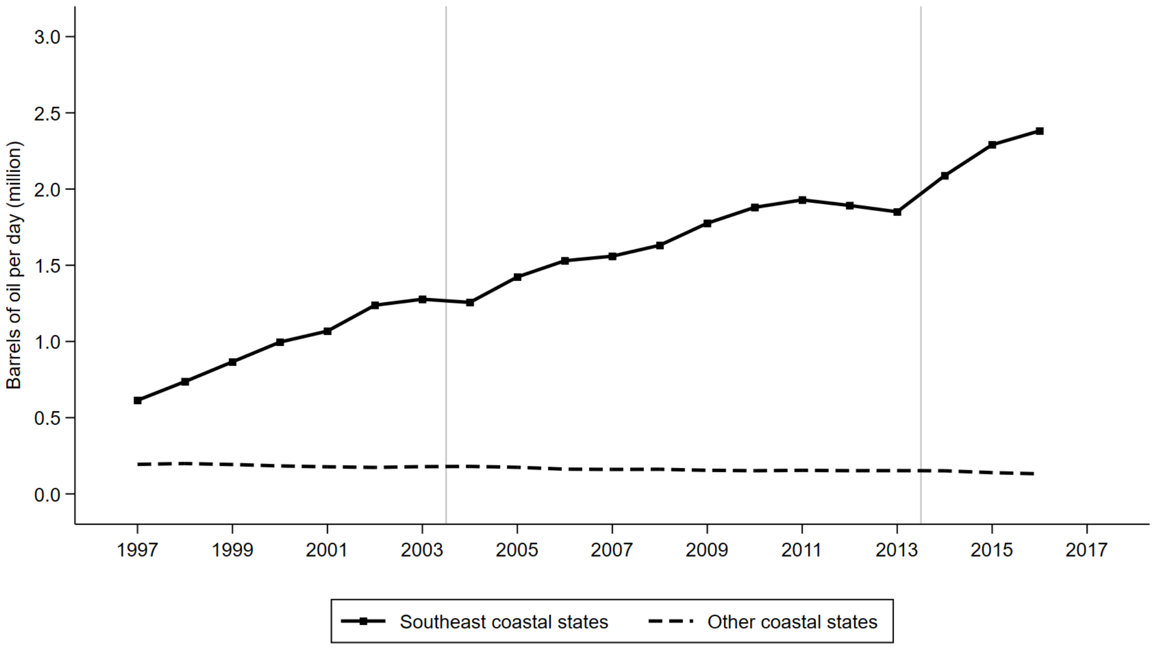

FIGURE A.1: OIL PRODUCTION, 1997-2016

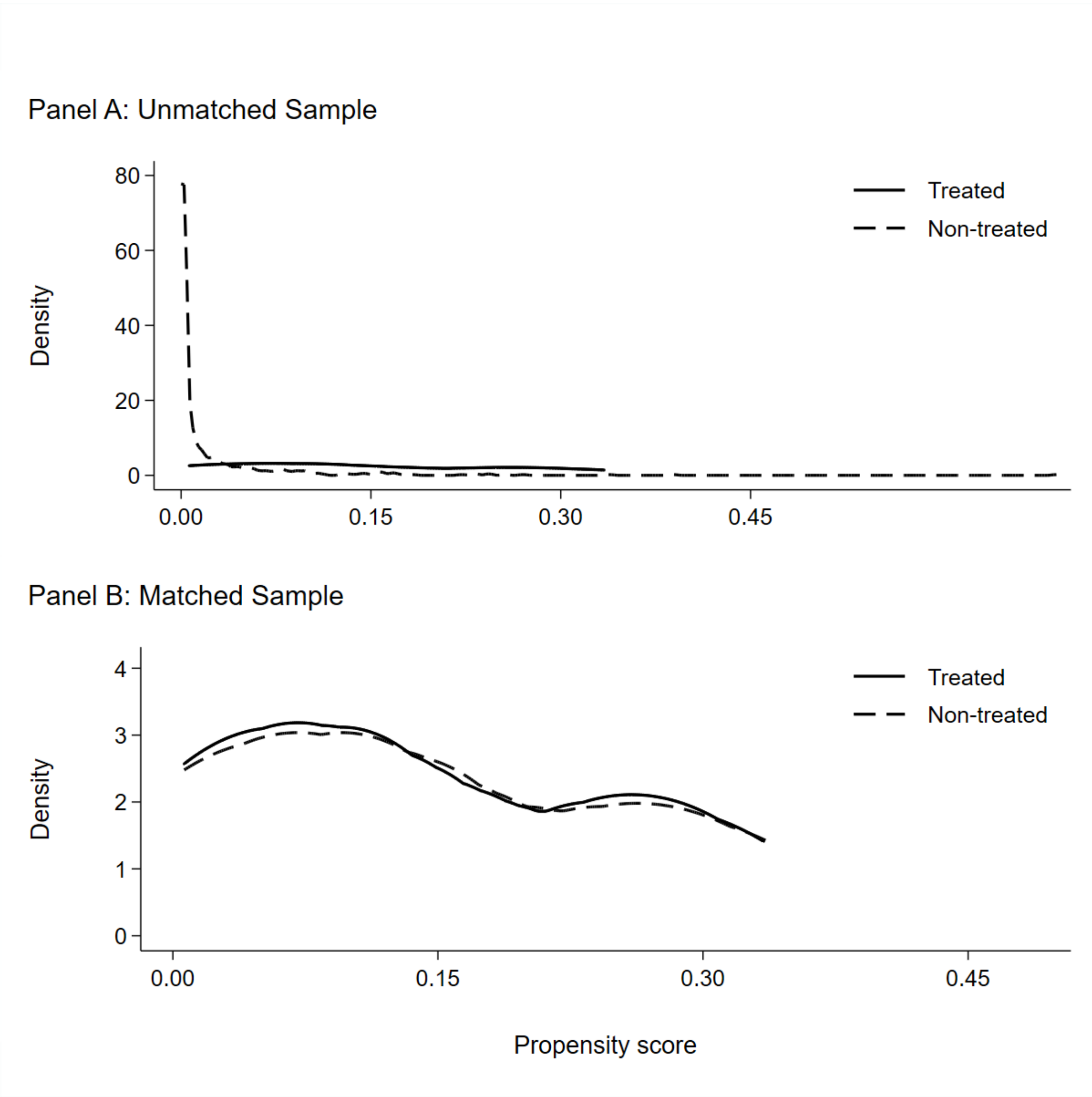

FIGURE A.2: PROPENSITY SCORE DISTRIBUTION

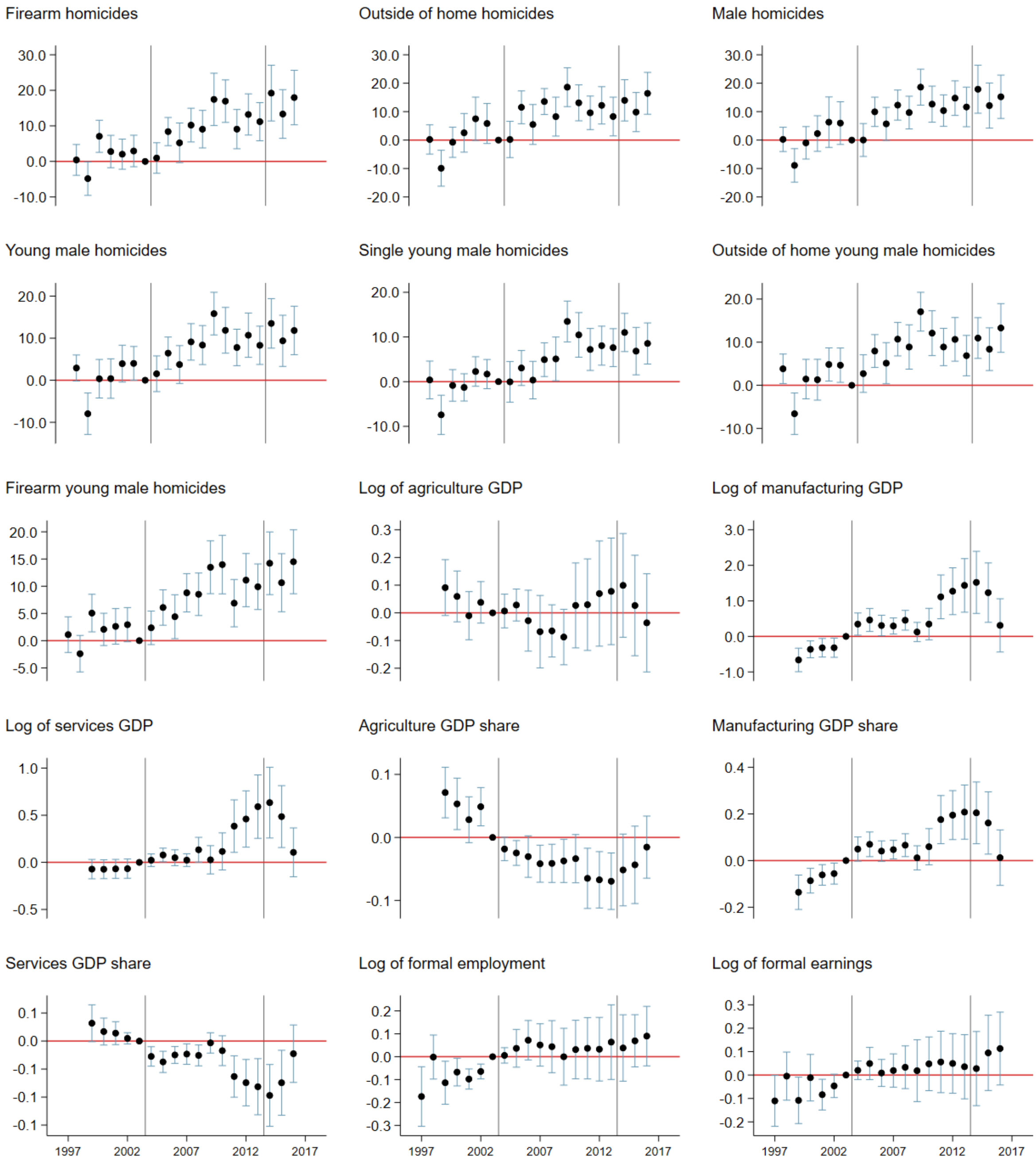

FIGURE A.3: DYNAMIC EFFECTS ON HOMICIDES CHARACTERISTICS, INCOME DECOMPOSITION, AND FORMAL LABOR MARKET OUTCOMES

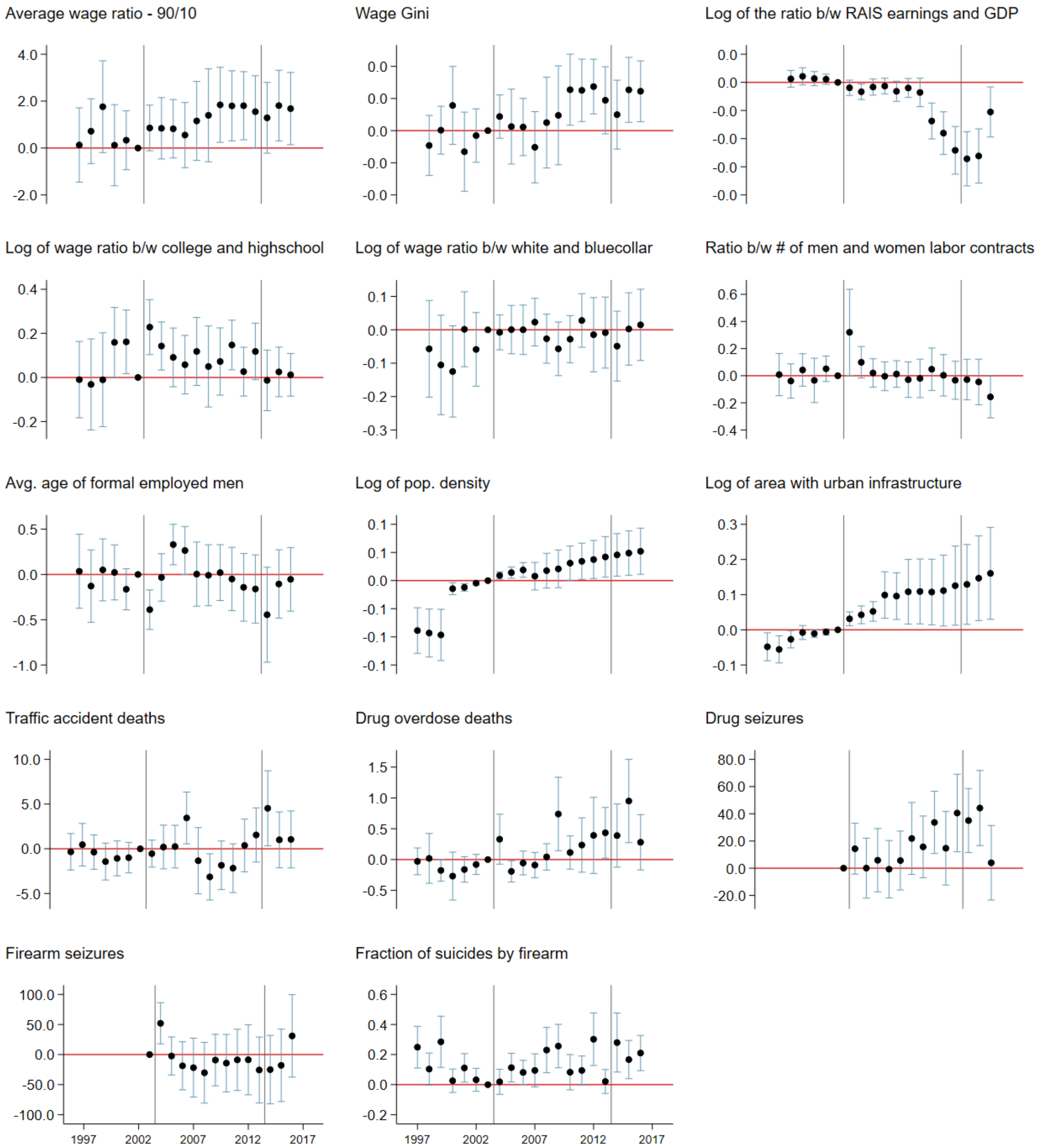

FIGURE A.4: DYNAMIC EFFECTS ON INEQUALITY, URBANIZATION, AND ILLEGAL MARKETS ACTIVITY

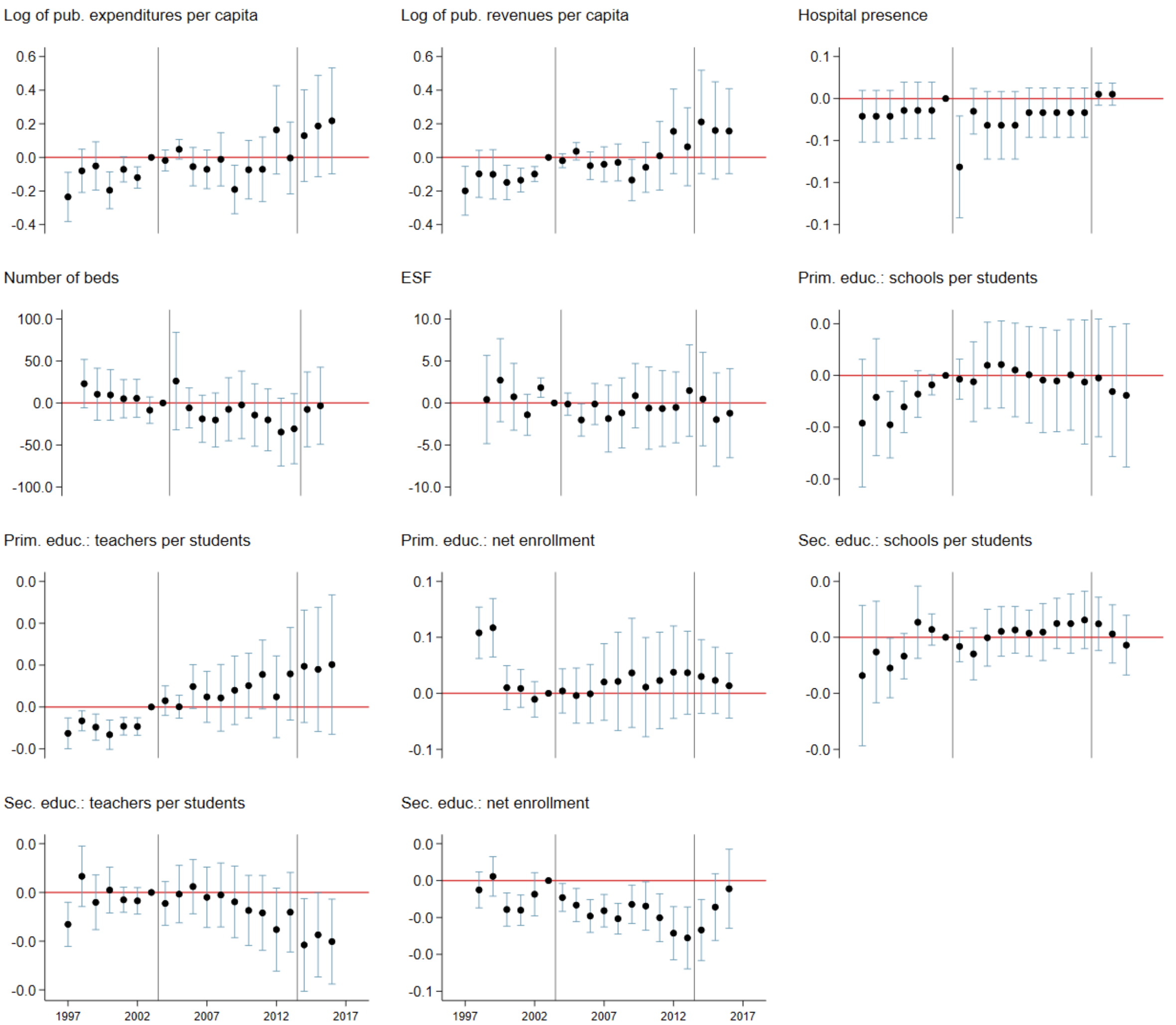

FIGURE A.5: DYNAMIC EFFECTS ON PUBLIC GOOD PROVISION

TABLE A.1: PROPENSITY SCORE ESTIMATION - PROBIT MODEL

	Coefficient	Standard Error
	(1)	(2)
Log of population	0.382***	[0.137]
Log of household income per capita	1.118	[1.965]
Share of urban population	1.758	[1.095]
Share of individuals below the poverty line	6.772	[5.239]
Gini coefficient	0.240	[6.403]
Share of individuals 20-39 years old	17.292*	[10.054]
Average years of schooling	−0.535	[0.483]
Share of employed in the manuf. sector	−9.750***	[3.246]
Share of employed in the oil sector	19.063	[12.725]
Constant	−18.460*	[9.984]
Observations	702	
Pseudo R-squared	0.32	

Notes: We report the latent model estimated coefficients in column (1). Standard errors are reported in brackets in column (2). Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $***$.

TABLE A.2: HOMICIDES AND INCOME DURING THE OIL BOOM AND BUST PERIODS - EQUATION (2) SPECIFICATION

	Homicides per 100,000 inhabitants			Log of GDP *per capita*		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Lagged oil price treatment						
well × log(lagged oil price)	13.236***	9.953***	9.971***	0.242	0.328**	0.376**
	[2.789]	[2.305]	[1.924]	[0.179]	[0.142]	[0.153]
Panel B: Contemporaneous oil price treatment						
well × log(oil price)	12.545***	9.371***	9.418***	0.300*	0.369**	0.415***
	[2.370]	[2.038]	[1.770]	[0.180]	[0.148]	[0.156]
State × Year FE		X	X		X	X
Baseline charact. × Year FE			X			X
Dep. variable mean	29.88	29.88	29.88	10.13	10.13	10.13
Observations	1,840	1,840	1,840	1,656	1,656	1,656

Notes: In brackets, standard errors are clustered at the AMC level. The sample includes AMCs from Brazil's coastal states of *São Paulo*, *Rio de Janeiro*, and *Espírito Santo*. All regressions are weighted by a function of the propensity score estimate $\hat{p}$. We include AMC fixed effects in all regressions and year fixed effects alone in columns (1) and (4). The baseline characteristics in columns (3) and (6) come from the 2000 Population Census and include the log of AMC's population, the lof of average household income per capita, the share of urban population, the fraction of individuals below the poverty line, Gini coefficient, the fraction of individuals in the 20-39 years old interval, average years of schooling, the share of formal employment in the manufacturing sector, and the share of formal employment in the oil sector. Due to data availability, columns (4)-(6) regression sample starts in 1999 while columns (1)-(3) uses data from the whole 1997-2016 period. Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $***$.

TABLE A.3: HOMICIDES AND INCOME DURING THE OIL BOOM AND BUST PERIODS - UNWEIGHTED SPECIFICATION

	Homicides per 100,000 inhabitants			Log of GDP *per capita*		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Boom and bust treatment						
well × boom period	18.196***	13.424***	11.921***	0.298***	0.275**	0.286***
	[4.380]	[4.195]	[4.098]	[0.103]	[0.107]	[0.107]
well × bust period	21.573***	17.412***	16.566***	0.230	0.212	0.238
	[5.141]	[5.160]	[5.108]	[0.231]	[0.240]	[0.238]
Panel B: Lagged oil price treatment						
well × log(lagged oil price)	15.642***	12.962***	12.190***	0.268**	0.253**	0.264**
	[3.546]	[3.518]	[3.309]	[0.111]	[0.114]	[0.114]
State × Year FE		X	X		X	X
Baseline charact. × Year FE			X			X
Dep. variable mean	13.47	13.47	13.47	10.15	10.15	10.15
Observations	14,040	14,040	14,040	12,636	12,636	12,636

Notes: In brackets, standard errors are clustered at the AMC level. The sample includes AMCs from Brazil's coastal states of *São Paulo*, *Rio de Janeiro*, and *Espírito Santo*. Regressions in columns (1), (2), and (3) are weighted by 2003 population. We include AMC fixed effects in all regressions and year fixed effects alone in columns (1) and (4). The baseline characteristics in columns (3) and (6) come from the 2000 Population Census and include the log of AMC's population, the log of average household income per capita, the share of urban population, the fraction of individuals below the poverty line, Gini coefficient, the fraction of individuals in the 20-39 years old interval, average years of schooling, the share of formal employment in the manufacturing sector, and the share of formal employment in the oil sector. Due to data availability, columns (4)-(6) regression sample starts in 1999 while columns (1)-(3) uses data from the whole 1997-2016 period. Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $***$.

TABLE A.4: HOMICIDES DECOMPOSITION BY LOCATION, WEAPON USED, AND VICTIMS CHARACTERISTICS - UNWEIGHTED SPECIFICATION

	Homicides			Male homicides		Male homicides, ages 15-39		
	All	Firearm	Outside of home	All ages	Ages 15-39	Single	Outside home	Firearm
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Boom and bust treatment								
well × boom period	11.921***	12.543***	11.077***	10.983***	9.581***	8.566***	9.255***	10.229***
	[4.098]	[3.440]	[3.725]	[3.723]	[2.461]	[2.004]	[2.370]	[2.243]
well × bust period	16.566***	19.408***	15.212***	14.987***	11.803***	11.062***	11.319***	14.398***
	[5.108]	[4.626]	[4.598]	[4.612]	[2.926]	[2.388]	[2.832]	[2.858]
Panel B: Lagged oil price treatment								
well × log(lagged oil price)	12.190***	12.573***	11.123***	11.178***	9.199***	8.725***	8.683***	9.757***
	[3.309]	[3.034]	[2.910]	[3.002]	[1.985]	[1.741]	[1.826]	[2.042]
Observations	14,040	14,040	14,040	14,040	14,040	14,040	14,040	14,040

Notes: In brackets, standard errors are clustered at the AMC level. The sample includes AMCs from Brazil's coastal states of *São Paulo*, *Rio de Janeiro*, and *Espírito Santo*. All regressions are weighted by 2003*population*. We include AMC fixed effects, state-year fixed effects, and the following controls, measured in the 2000 Population Census and interacted with a full set of year dummies, in all regressions: the log of AMC's population, the log of average household income per capita, the share of urban population, the fraction of individuals below the poverty line, Gini coefficient, the fraction of individuals in the 20-39 years old interval, average years of schooling, the share of formal employment in the manufacturing sector, and the share of formal employment in the oil sector. Regression samples in all columns use data from the whole 1997-2016 period. Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $* * *$.

TABLE A.5: INCOME SPILLOVER EFFECTS AND FORMAL LABOR MARKET OUTCOMES - UNWEIGHTED SPECIFICATION

			Log of sectoral GDP			GDP shares			Employment and earnings	
	Log of GDP	Log of GDP *per cap*	Agriculture	Manuf.	Services	Agriculture	Manuf.	Services	Log of employment	Log of earnings
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Boom and bust treatment										
well × boom period	0.372***	0.286***	−0.055	0.688***	0.252***	−0.025*	0.103***	−0.038***	0.119*	0.071*
	[0.105]	[0.107]	[0.082]	[0.182]	[0.092]	[0.014]	[0.027]	[0.012]	[0.061]	[0.039]
well × bust period	0.388	0.238	−0.083	0.699*	0.298	−0.027	0.092	−0.039	0.150*	0.095
	[0.238]	[0.238]	[0.150]	[0.421]	[0.194]	[0.022]	[0.057]	[0.029]	[0.084]	[0.071]
Panel B: Lagged oil price treatment										
well × log(lagged oil price)	0.349***	0.264**	−0.026	0.618***	0.259***	−0.019	0.091***	−0.032**	0.099*	0.058
	[0.114]	[0.114]	[0.077]	[0.191]	[0.095]	[0.013]	[0.027]	[0.013]	[0.054]	[0.039]
Observations	12,636	12,636	12,600	12,634	12,636	12,636	12,636	12,636	14,040	14,040

Notes: In brackets, standard errors are clustered at the AMC level. The sample includes AMCs from Brazil's coastal states of *São Paulo*, *Rio de Janeiro*, and *Espírito Santo*. We include AMC fixed effects, state-year fixed effects, and the following controls, measured in the 2000 Population Census and interacted with a full set of year dummies, in all regressions: the log of AMC's population, the log of average household income per capita, the share of urban population, the fraction of individuals below the poverty line, Gini coefficient, the fraction of individuals in the 20-39 years old interval, average years of schooling, the share of formal employment in the manufacturing sector, and the share of formal employment in the oil sector. Due to data availability, columns (1)-(8) regression sample starts in 1999 while columns (9)-(10) uses data from the whole 1997-2016 period. Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $***$.

TABLE A.6: HOMICIDES BY TYPE OF AGGRESSION

		Decomposition					
	All homicides	Physical aggression	Fire and chemicals	Firearms	Knives or cutting instruments	Unspecified	Police interventions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Boom and bust treatment							
well × boom period	9.836***	0.048	0.068	8.691***	2.333***	−1.244	−0.061
	[2.553]	[0.141]	[0.089]	[1.735]	[0.733]	[1.311]	[0.104]
well × bust period	15.576***	−0.172	0.235**	15.358***	1.938**	−1.496	−0.287*
	[3.112]	[0.195]	[0.115]	[3.351]	[0.825]	[1.471]	[0.158]
Panel B: Lagged oil price treatment							
well × log(lagged oil price)	9.971***	−0.003	0.137**	8.308***	1.999***	−0.391	−0.080
	[1.924]	[0.113]	[0.065]	[1.675]	[0.526]	[0.933]	[0.069]
Observations	1,840	1,840	1,840	1,840	1,840	1,840	1,840

Notes: In brackets, standard errors are clustered at the AMC level. The sample includes AMCs from Brazil's coastal states of *São Paulo*, *Rio de Janeiro*, and *Espírito Santo.* All regressions are weighted by a function of the propensity score estimate $\hat{p}$. We include AMC fixed effects, state-year fixed effects, and the following controls, measured in the 2000 Population Census and interacted with a full set of year dummies, in all regressions: the log of AMC's population, the log of average household income per capita, the share of urban population, the fraction of individuals below the poverty line, Gini coefficient, the fraction of individuals in the 20-39 years old interval, average years of schooling, the share of formal employment in the manufacturing sector, and the share of formal employment in the oil sector. Regression samples in all columns use data from the whole 1997-2016 period. Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $***$.

TABLE A.7: HOMICIDES LOCATION

		Decomposition					
	Outside of home homicides	Schools and public buildings	Sports and industrial areas	Roads and streets	Retail and services areas	Farms	Unspecified
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Boom and bust treatment							
well × boom period	9.307***	−0.021	−0.005	5.487***	0.380	−0.033	3.500
	[2.509]	[0.123]	[0.083]	[1.945]	[0.261]	[0.050]	[3.099]
well × bust period	12.642***	0.067	−0.029	9.792***	0.409	−0.055	2.458
	[2.617]	[0.053]	[0.032]	[3.223]	[0.302]	[0.058]	[3.416]
Panel B: Lagged oil price treatment							
well × log(lagged oil price)	8.455***	0.024	0.005	5.584***	0.422	−0.055	2.474
	[1.767]	[0.082]	[0.074]	[1.887]	[0.283]	[0.046]	[2.372]
Observations	1,840	1,840	1,840	1,840	1,840	1,840	1,840

Notes: In brackets, standard errors are clustered at the AMC level. The sample includes AMCs from Brazil's coastal states of *São Paulo*, *Rio de Janeiro*, and *Espírito Santo*. All regressions are weighted by a function of the propensity score estimate $\hat{p}$. We include AMC fixed effects, state-year fixed effects, and the following controls, measured in the 2000 Population Census and interacted with a full set of year dummies, in all regressions: the log of AMC's population, the log of average household income per capita, the share of urban population, the fraction of individuals below the poverty line, Gini coefficient, the fraction of individuals in the 20-39 years old interval, average years of schooling, the share of formal employment in the manufacturing sector, and the share of formal employment in the oil sector. Regression samples in all columns use data from the whole 1997-2016 period. Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $***$.

TABLE A.8: SECTORAL EMPLOYMENT IN THE FORMAL LABOR MARKET

	Sectoral employment													
	Agriculture	Mining	Constr.	Financial sector	Food & hotel	Manuf. ex-oil	Oil & gas extraction	Oil refining	Private services	Public adm.	Real estate	Transp.	Utilities	Wholesale & retail
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel A: Boom and bust treatment														
well × boom period	0.341**	0.362	0.496*	0.185***	0.195**	−0.411**	−0.014	−0.362**	0.046	0.214*	−0.240**	−0.020	−0.370	−0.003
	[0.164]	[0.243]	[0.252]	[0.067]	[0.094]	[0.167]	[0.238]	[0.148]	[0.089]	[0.121]	[0.118]	[0.115]	[0.306]	[0.046]
well × bust period	0.202	1.301***	0.139	0.370***	0.058	−0.413**	0.202	−0.456**	0.026	0.420***	−0.250	−0.179	−0.720*	0.010
	[0.177]	[0.270]	[0.363]	[0.098]	[0.137]	[0.164]	[0.363]	[0.197]	[0.123]	[0.158]	[0.169]	[0.227]	[0.410]	[0.071]
Panel B: Lagged oil price treatment														
well × log(lagged oil price)	0.240*	0.443**	0.270	0.191***	0.109	−0.277**	0.040	−0.343**	−0.042	0.243**	−0.216*	−0.165	−0.354	−0.002
	[0.123]	[0.183]	[0.222]	[0.061]	[0.079]	[0.124]	[0.206]	[0.140]	[0.078]	[0.095]	[0.110]	[0.121]	[0.251]	[0.040]
Observations	1,840	1,840	1,840	1,840	1,840	1,840	1,840	1,840	1,840	1,840	1,840	1,840	1,840	1,840

Notes: In brackets, standard errors are clustered at the AMC level. The sample includes AMCs from Brazil's coastal states of *São Paulo*, *Rio de Janeiro*, and *Espírito Santo*. All regressions are weighted by a function of the propensity score estimate $\hat{p}$. We include AMC fixed effects, state-year fixed effects, and the following controls, measured in the 2000 Population Census and interacted with a full set of year dummies, in all regressions: the log of AMC's population, the log of average household income per capita, the share of urban population, the fraction of individuals below the poverty line, Gini coefficient, the fraction of individuals in the 20-39 years old interval, average years of schooling, the share of formal employment in the manufacturing sector, and the share of formal employment in the oil sector. Regression samples in all columns use data from the whole 1997-2016 period. Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $***$.

TABLE A.9: LOCAL PUBLIC FINANCE NET OF OIL ROYALTIES

	Log of GDP ex-Royalties		Log of pub. revenues ex-Royalties		Log of pub. expenditures ex-Royalties	
	Level	*Per capita*	Level	*Per capita*	Level	*Per capita*
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Boom and bust treatment						
well × boom period	0.397***	0.348**	0.125**	0.066	0.033	–0.026
	[0.134]	[0.136]	[0.051]	[0.050]	[0.032]	[0.034]
well × bust period	0.652**	0.578**	0.269**	0.189	0.182	0.101
	[0.272]	[0.280]	[0.120]	[0.123]	[0.112]	[0.113]
Panel B: Lagged oil price treatment						
well × log(lagged oil price)	0.426***	0.380**	0.117*	0.066	0.033	–0.019
	[0.149]	[0.153]	[0.064]	[0.066]	[0.045]	[0.047]
Observations	1,656	1,656	1,730	1,730	1,726	1,726

Notes: In brackets, standard errors are clustered at the AMC level. The sample includes AMCs from Brazil's coastal states of *São Paulo*, *Rio de Janeiro*, and *Espírito Santo*. All regressions are weighted by a function of the propensity score estimate $\hat{p}$. We include AMC fixed effects, state-year fixed effects, and the following controls, measured in the 2000 Population Census and interacted with a full set of year dummies, in all regressions: the log of AMC's population, the log of average household income per capita, the share of urban population, the fraction of individuals below the poverty line, Gini coefficient, the fraction of individuals in the 20-39 years old interval, average years of schooling, the share of formal employment in the manufacturing sector, and the share of formal employment in the oil sector. Due to data availability, columns (1)-(2) regression sample starts in 1999 while columns (3)-(6) uses data from the whole 1997-2016 period. Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $***$.

TABLE A.10: POPULATION ROBUSTNESS ESTIMATIONS, 2000-2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Main results		Mechanisms					Public Goods			
	Homicides per 100,000 inhabitants	Log of GDP *per capita*	Log of pop. density	Traffic accident deaths per 100,000 inhab.	Drug overdose deaths per 100,000 inhab.	Drug seizures per 100,000 inhab.	Firearm seizures per 100,000 inhab.	Log of public expenditures *per cap.*	Log of public revenues *per cap.*	# of beds per 100,000 inhab.	ESF per 100,000 inhab.
Panel A: Boom and bust treatment											
well × boom period	6.503*	0.343**	0.031**	0.552	0.322***	15.162	−8.783	0.065	0.086	−13.369	−0.768
	[3.347]	[0.137]	[0.013]	[1.193]	[0.094]	[12.189]	[23.100]	[0.065]	[0.066]	[24.090]	[1.660]
well × bust period	12.243***	0.574**	0.057**	3.067	0.667***	27.745*	−3.983	0.272*	0.267*	−5.982	−1.199
	[3.477]	[0.285]	[0.024]	[1.892]	[0.169]	[14.896]	[36.264]	[0.161]	[0.154]	[30.359]	[2.776]
Panel B: Lagged oil price treatment											
well × log(lagged oil price)	8.491***	0.425**	0.031**	0.955	0.426***	23.858***	−33.801	0.082	0.108	−15.866	−0.289
	[2.564]	[0.176]	[0.015]	[0.992]	[0.101]	[8.472]	[27.036]	[0.086]	[0.092]	[17.666]	[1.785]
Observations	1,564	1,564	1,564	1,564	1,564	938	938	1,498	1,497	1,472	1,564
	Main results		Mechanisms					Public Goods			
	Homicides per 100,000 inhabitants	Log of GDP *per capita*	Log of pop. density	Traffic accident deaths per 100,000 inhab.	Drug overdose deaths per 100,000 inhab.	Drug seizures per 100,000 inhab.	Firearm seizures per 100,000 inhab.	Log of public expenditures *per cap.*	Log of public revenues *per cap.*	# of beds per 100,000 inhab.	ESF per 100,000 inhab.
Panel C: Boom and bust treatment											
well × boom period	6.544*	0.343**	0.032**	0.626	0.329***	15.400	−8.809	0.065	0.086	−14.807	−0.696
	[3.412]	[0.139]	[0.014]	[1.196]	[0.095]	[12.323]	[23.925]	[0.066]	[0.067]	[24.234]	[1.735]
well × bust period	12.601***	0.570**	0.061**	3.062	0.704***	29.258*	−4.067	0.267	0.262*	−8.255	−1.454
	[3.629]	[0.285]	[0.027]	[1.926]	[0.184]	[14.669]	[37.775]	[0.160]	[0.153]	[30.791]	[2.847]
Panel D: Lagged oil price treatment											
well × log(lagged oil price)	8.552***	0.421**	0.035**	0.990	0.436***	24.202***	−35.192	0.079	0.104	−17.329	−0.342
	[2.689]	[0.176]	[0.015]	[1.009]	[0.101]	[8.378]	[28.762]	[0.085]	[0.090]	[17.786]	[1.850]
Observations	1,564	1,564	1,564	1,564	1,564	938	938	1,498	1,497	1,472	1,564

Notes: Panels A and B show the estimations using IBGE population data whereas panels C and D use WorldPop data as robustness. In brackets, standard errors are clustered at the AMC level. The sample includes AMCs from Brazil's coastal states of *São Paulo*, *Rio de Janeiro*, and *Espírito Santo*. All regressions are weighted by a function of the propensity score estimate $\hat{p}$. We include AMC fixed effects, state-year fixed effects, and the following controls, measured in the 2000 Population Census and interacted with a full set of year dummies, in all regressions: the log of AMC's population, the log of average household income per capita, the share of urban population, the fraction of individuals below the poverty line, Gini coefficient, the fraction of individuals in the 20-39 years old interval, average years of schooling, the share of formal employment in the manufacturing sector, and the share of formal employment in the oil sector. Given the availability of the WorldPop data, we restricted the regression sample in all columns to the 2000-2016 interval. Significance at the 10% level is represented by $*$, at the 5% level by $**$, and at the 1% level by $***$.