

Christensen, Hans B.; Maffett, Mark; Rauter, Thomas

**Working Paper**

## Reversing the Resource Curse: Foreign Corruption Regulation and Economic Development

Working Paper Series, No. 304

**Provided in Cooperation with:**

George J. Stigler Center for the Study of the Economy and the State, The University of Chicago  
Booth School of Business

*Suggested Citation:* Christensen, Hans B.; Maffett, Mark; Rauter, Thomas (2020) : Reversing the Resource Curse: Foreign Corruption Regulation and Economic Development, Working Paper Series, No. 304, University of Chicago Booth School of Business, Stigler Center for the Study of the Economy and the State, Chicago, IL

This Version is available at:

<https://hdl.handle.net/10419/262706>

**Standard-Nutzungsbedingungen:**

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

**Terms of use:**

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*



**Stigler Center**

for the Study of the Economy and the State

**Reversing the Resource Curse:  
Foreign Corruption Regulation and Economic  
Development**

Hans B. Christensen

University of Chicago Booth School of Business

Mark Maffett

University of Chicago Booth School of Business

Thomas Rauter

University of Chicago Booth School of Business

October 2020

Working Paper Series No. 304

Stigler Center for the Study of the Economy and the State  
University of Chicago Booth School of Business  
5807 S Woodlawn Ave  
Chicago, IL 60637

# Reversing the Resource Curse: Foreign Corruption Regulation and Economic Development

By HANS B. CHRISTENSEN, MARK MAFFETT, and THOMAS RAUTER\*

October 2020

## Abstract:

We examine the impact of foreign corruption regulation on economic development in high-corruption-risk areas. We find that, after a mid-2000s increase in enforcement of the US Foreign Corrupt Practices Act (FCPA), economic activity (measured by nighttime luminosity) in African communities within a 50-kilometer radius of natural resource extraction facilities subject to the FCPA increases by 8%. Local perceptions of corruption also significantly decline. Consistent with the increase in economic activity being driven, at least in part, by existing extraction firms shifting to business practices that are more beneficial to the local communities where they operate, the association between resource production and local economic activity increases by 37%. Overall, our findings suggest that anti-corruption regulation originating in developed countries is effective in changing corporate behavior and has a positive economic impact in developing countries.

**Keywords:** Foreign Corruption Regulation; Foreign Corrupt Practices Act (FCPA); Economic Development; Natural Resource Extraction

**JEL Classification:** F50; F60; K2; M4; O1

---

\* University of Chicago Booth School of Business, 5807 South Woodlawn Avenue Chicago, IL 60637 ([hans.christensen@chicagobooth.edu](mailto:hans.christensen@chicagobooth.edu); [mark.maffett@chicagobooth.edu](mailto:mark.maffett@chicagobooth.edu); [thomas.rauter@chicagobooth.edu](mailto:thomas.rauter@chicagobooth.edu)). We thank Mia Giuriato and Ginha Kim for outstanding research assistance. We appreciate helpful comments from workshop participants at the University of Chicago and the University of Mannheim. We gratefully acknowledge financial support from the University of Chicago Booth School of Business. This work is also supported by the Asness Junior Faculty Fellowship, the David G. Booth Faculty Fellowship, the IBM Corporation Faculty Fellowship, the John E. Jeuck Faculty Fellowship, and the Neubauer Family Faculty Fellowship at the University of Chicago Booth School of Business.

## 1. Introduction

Countries with large natural-resource endowments are often less developed and more poorly governed than countries with fewer resources, a phenomenon economists and policymakers call the “resource curse” (Auty 1993; Sachs and Warner 1995). Corruption plays a central role in the resource curse because the need to secure access rights to deposits around the world makes resource extraction (i.e., precious metal mining and oil drilling) inherently prone to corruption (Robinson et al. 2006).<sup>1</sup> Although the direct effect of resource extraction on economic activity is likely positive (Smith 2015; Mamo et al. 2019), corruption in the extraction sector can divert resources from local development projects, decrease the efficiency of resource allocation, and reinforce extractive political regimes (Shleifer and Vishny 1993; Acemoglu and Robinson 2012; Ortiz-Ospina and Roser 2016), attenuating any positive effects of extractive activities.

Recognizing the costs of corruption in the developing world, governments in many developed countries have enacted regulation to curb corrupt business practices (e.g., Karpoff et al. 2017; Zeume 2017)—the most prominent and widely enforced being the US Foreign Corrupt Practices Act (FCPA). US enforcement of the FCPA against both US and non-US firms under US jurisdiction has increased dramatically since 2005 (Martin et al. 2012; Olken and Pande 2012). While the ostensible objective of foreign corruption regulation is to reduce the supply-side incentives to engage in corrupt activities, prior research shows that one consequence of the compliance costs imposed by anti-corruption regulation is a reduction in foreign direct investment in high-corruption-risk countries (e.g., Beck et al. 1991; Hines 1995; Cuervo-Cazurra 2006; Christensen et al. 2020). Some business leaders argue that without the ability to bribe government officials it is hard to operate in countries with inefficient bureaucracies. If the costs imposed by foreign corruption regulation lead to a reduction in economically beneficial foreign investment, or the inability to pay bribes prevents regulated firms from competing against less efficient unregulated firms, foreign corruption regulation could have a negative impact on economic development in high-corruption-risk areas.

Yet, the net economic impact of foreign corruption regulation also depends on how much the regulation decreases corruption, what regulated firms do instead of paying bribes, and whether

---

<sup>1</sup> Other explanations for the resource curse include real exchange rate appreciation that negatively affects the tradable non-resource sector (Cordon and Neary 1982) and commodity price volatility that exposes resource-rich countries to global shocks (Ramey and Ramey 1995; Deaton 1999).

the marginal investments forgone because of the regulation would have had a positive impact on development. For instance, anti-corruption regulation could force firms to stop engaging in activities that require paying bribes and have a negative economic impact on the local community (e.g., polluting local water sources). Moreover, in the absence of the ability to pay bribes, firms that remain engaged in high-corruption-risk countries may seek alternative ways to minimize conflict with the local population, such as hiring more local workers or contributing to local infrastructure projects (Aragon and Rud 2013). If foreign corruption regulation reduces corruption and mitigates negative aspects of resource extraction, it could foster economic development in high-corruption-risk areas.

To speak to the impact of foreign corruption regulation, we examine changes in economic activity, as measured by nighttime light emissions (i.e., luminosity), in African communities near large resource extraction facilities following a plausibly-exogenous increase in US FCPA enforcement in the mid-2000s. In our research design, we exploit the fact that, for reasons related to the feasibility of enforcement, FCPA cases are almost exclusively limited to firms under US jurisdiction that are headquartered in OECD countries (Christensen et al. 2020). Consequently, the enforcement shock likely impacts only the subset of African communities located near extraction facilities with an ultimate beneficial owner that is under US jurisdiction and headquartered in an OECD country. This feature of the setting allows us to estimate the treatment effect of foreign corruption regulation benchmarked against a control sample of likely unaffected communities (i.e., those located near an extraction facility with an owner that is not subject to the FCPA).

A recent enforcement action against Halliburton, an SEC-registered oilfield-services corporation headquartered in Houston, Texas, provides an illustrative example of how the FCPA could curb corruption and increase the local economic benefits of resource extraction.<sup>2</sup> In 2008, government officials in Angola informed the company that they were considering vetoing further work by Halliburton in Angola because the company had not meet its local content obligations.<sup>3</sup> In an effort to fulfill these obligations, a Halliburton executive arranged for the company to outsource services to a local Angolan logistical-services company owned by a friend and neighbor

---

<sup>2</sup> See, *In the Matter of Halliburton Company and Jeannot Lorenz* (2017) for case details.

<sup>3</sup> Many developing countries impose “local content obligations” on foreign businesses, with the aim of increasing the local benefits of resource extraction. These regulations typically require foreign companies to source certain goods and services from local enterprises and provide training to their employees as a condition of their operating licenses (see UNCTAD 2012 for details).

of an Angolan official who had the authority to veto Halliburton's work authorization. A contract with the government-affiliated contractor was signed despite concerns raised in Halliburton's own internal evaluation, which indicated that other, more qualified local firms could have provided the services at a lower cost. Halliburton's local content proposal was subsequently approved by the Angolan government, even though much of the agreed upon work was never performed. Because of the political connection to the Angolan official and because the contracts included inaccurate information, the arrangement violated the FCPA.

As the Halliburton example shows, if the FCPA discourages the allocation of contracts to inefficient service providers and compels foreign firms to fulfill their financial obligations to host countries through legitimate means, it could boost development, both through additional payments and because of the resource allocation implications of picking the most efficient rather than most politically connected partner. Moreover, because FCPA compliance typically necessitates third-party audits of potential contracting partners, it also creates an incentive for local firms hoping to transact with foreign firms to avoid perceptions of corruption, even when engaging with firms that are not subject to the FCPA (e.g., to avoid appearing on commonly used corruption watch lists that would preclude them from working with firms subject to the FCPA). Given the large economic influence extraction firms have on the surrounding communities, the indirect effects of the FCPA on local firms could be significant.

Our study focuses on the extraction industry in Africa, which is a powerful setting to examine the impact of foreign corruption regulation on economic development because resource extraction comprises a significant proportion of the African economy and foreign corporations play a major role in these activities (Chuhan-Pole et al. 2017). We measure economic activity using satellite images depicting the density of nighttime light emissions measured at levels of spatial stratification from 10- to 100-kilometers around an extraction facility. In rural Africa, nighttime luminosity is highly associated with economic activities, which provides us with reliable, uniform estimates of development in highly localized areas (Henderson et al. 2012; Michalopoulos and Papaioannou 2014; Mamo et al. 2019). Compared to other measures of economic development (e.g., GDP), luminosity reflects the level of economic activity more broadly, and thus is likely more indicative of the overall well-being of people throughout the community. We combine the luminosity data with location, ownership, and commodity-type data for extraction facilities across Africa from SNL Metals and Mining ("SNL") and Enverus

International (“Enverus”) and focus on active extraction areas with positive reported production in at least one year of our sample period. This high degree of spatial resolution allows us to assess the impact of foreign corruption regulation at the local level, where it is most plausible that firm activities could significantly affect economic conditions. To alleviate concerns about endogenous extraction site openings, closings, and ownership changes, we determine whether the facility’s owner was subject to the FCPA in 2004 (i.e., before the FCPA enforcement increase).

We find that, in the years after 2004, geographic areas with an extraction facility whose owner is subject to the FCPA gradually exhibit higher levels of economic activity relative to areas surrounding extraction sites that are not subject to the regulation. As we increase the length of the radius of the cell surrounding the extraction site, the estimated treatment effect monotonically declines; falling from a 40% increase in luminosity within 10 kilometers of the site (where the extraction industry plays a central role in the economy, directly employing nearly 20% of the total workforce) to an increase of 2% within 100 kilometers. Our results are robust to excluding luminosity emanating directly from the extraction facility itself and controlling for regional time trends. The effects are not present for extraction areas that are economically similar to our treatment group, but rarely targeted by FCPA enforcement actions (i.e., firms under US jurisdiction but headquartered in non-OECD countries).

To the extent that corruption negatively affects economic development, the observed increase in local economic activity following the increase in FCPA enforcement could be explained (in part) by a reduction in corruption. Yet, measuring corruption is difficult given the incentives of both the bribe payer and receiver to conceal their corrupt activities. As an alternative, we use microdata on local residents’ perceptions of corruption from the Afrobarometer survey. Our results indicate that individuals living near extraction sites whose owners are subject to the FCPA are 8% less likely to perceive their government as corrupt after 2004.

Further analyses indicate that the observed positive association between foreign corruption regulation and economic development is not explained by a decline in activity in the extraction sector (i.e., we find that production and employment levels in the extraction sector remain relatively stable). This suggests the observed increase in development and reduction in perceived corruption are driven (at least in part) by a change in how firms in and around the extractive sector behave. To assess this possibility, we estimate the contribution of extraction firms’ activities to economic development. If, as a result of foreign corruption regulation, extraction firms engage in

activities that are more beneficial (or less detrimental) to the local community, we expect the association between resource production and economic activity to increase. To mitigate concerns about the endogeneity of production decisions, we use variation in world commodity prices as an instrument for production quantities. We find that the introduction of foreign corruption regulation increases the elasticity of luminosity to world commodity prices by 37% within a 10-kilometer radius of an extraction site. The change in elasticity declines predictably as we increase the radius of the extraction area, but remains statistically significant for distances up to 50-kilometers. Additional analyses indicate that the increased contribution of the extraction sector to local economic activity is not explained by ownership changes (i.e., new, less corrupt firms moving in).

Taken together, our analyses suggest that the increase in development in areas subject to foreign corruption regulation is driven (at least in part) by existing extraction firms engaging in activities that are more beneficial to the local communities surrounding their operations. Although micro-level data on most facility-level firm activities are unavailable, plausible changes include these firms no longer engaging in locally detrimental activities that require bribes (e.g., polluting), increased pay and training of local workers, more support for local infrastructure projects (e.g., roads), hiring contractors based on efficiency rather than political connections, and promoting a widespread reduction in corruption throughout their supply chain to ensure compliance with the FCPA's internal control requirements.

Our findings contribute most directly to the literature on anti-corruption regulation. Most prior work focuses on foreign corruption regulation's impact on the operations of multinational corporations (e.g., Graham 1984, Beck et al 1991; Hines 1995; Zeume 2017; Christensen et al. 2020; Rauter 2020). We instead provide evidence on how foreign corruption regulation impacts economic activity in the host countries where bribes are paid, and where the negative consequences of corruption are most acutely felt. Some prior studies examine the effects of domestic corruption regulation on corruption (Olken 2007; Ferraz and Finan 2008; Bobonis et al. 2013; Zamboni et al. 2018; Avis et al. 2016) and on local firm behavior and economic growth (Colonnelli and Prem 2020). In contrast, we examine how foreign corruption regulation, originating in developed countries, affects local economic conditions in the developing world. Reducing foreign corruption by multinational corporations is likely more difficult than prosecuting domestic corruption because it is challenging for local law enforcement, especially in developing countries with weak institutions, to gather evidence and sanction perpetrators located abroad. Our evidence indicates



that, despite any increase in the costs of operating in high-corruption-risk countries, foreign corruption regulation stimulates economic development by changing the way foreign firms operate and interact with local communities.

Our results are also related to a large literature that examines the impact of resource extraction on economic development, beginning with the finding by Sachs and Warner (1995) that countries rich in natural resources tend to experience lower economic growth (i.e., the “resource curse”). Although most recent work does not support an overall negative impact of natural resources on economic growth (e.g., Smith 2015; Mamo et al. 2019), many argue that the local benefits from natural resources are less than one would expect and that the institutions of host countries explain divergent outcomes (e.g., Mehlum et al. 2006; Robinson et al. 2006; Humphreys et al. 2007; Sarr et al. 2011). Our results suggest that anti-corruption regulation imposed on multinational corporations by countries with strong institutions (in this case the US) can increase the contribution of resource extraction to local economic development in high-corruption-risk countries with weak institutions.

## **2. Foreign Corruption Regulation, Corruption, and Economic Development in Natural Resource Extraction Areas**

Foreign corruption regulation has the potential to significantly increase the costs of engaging in corruption and affect economic development in African communities where the resource extraction industry plays a major role. There are (at least) four reasons why.

First, prior research finds that, in an effort to avoid sanctions for corrupt activities, foreign corruption regulation can lead multinational firms to make substantial changes to their operations. These include changes to their organizational structure (Zeume 2017; Sanseverino 2020), where they sell their products (Beck, Maher, and Tschoegl 1991), and their investment policies (Hines 1995; Cuervo-Cazurra 2006; 2008; D’Souza 2012; Blundell-Wignall and Roulet 2017; Christensen et al. 2020; Rauter 2020). Such substantial, and presumably costly, changes have generally been documented in settings where the regulatory shock was small compared to the mid-2000s increase in US FCPA enforcement (discussed in Section 3). Moreover, foreign multinationals are important players in the extraction industry in Africa. Table 1 reports that 41% of properties in our sample are owned by foreign firms, and among the foreign-owned mines, 87% are under US jurisdiction and 39% are under US jurisdiction and headquartered in an OECD country (i.e., subject to foreign corruption regulation under the FCPA).

Second, in resource-rich areas of Africa, the extraction sector is of central importance to the local economies where extraction firms operate, and any change in these firms' activities is likely to have a major impact. Using occupational microdata from the 2004 *Afrobarometer* survey (see Section 5 for details), in Table 2 Panel A, we estimate that, within a 10-kilometer radius of an extraction site, 18% of the local workforce is employed in the extraction industry. This proportion monotonically decreases to 7% as the radius is extended to 100 kilometers. In communities we do not classify as extraction areas, the fraction of mine workers is only 0.5%.

Third, because the extraction sector is prone to corrupt business practices, it is a frequent target of anti-corruption enforcement. Survey data from *Afrobarometer* in Table 2 Panel B show that residents of resource-dependent communities are significantly more likely to perceive foreign businessmen as corrupt relative to residents of non-resource-dependent communities. Consistent with widespread corruption, nearly 20% of all foreign bribery cases worldwide, more than any other industry, involve companies in the extraction sector (OECD 2014). Approximately 15% of all FCPA enforcement actions over the past 15 years relate to violations by extraction firms in Africa (Stanford FCPA Database 2020).

Fourth, the FCPA creates an incentive for local third parties that plan to work with firms subject to the regulation (e.g., construction firms) to avoid engaging in corrupt activities, even in transactions with firms that are not subject to the regulation. For example, besides prohibiting bribery, the FCPA also imposes recordkeeping requirements that force firms to ensure their internal controls can prevent and detect improper payments, such as those made to firms with a reputation for engaging in corrupt activities. To ensure compliance with the FCPA's accounting provisions, firms typically perform third-party due diligence of suppliers and service providers (Huskins 2008). Third-party due diligence involves screening new and existing business partners for possible affiliations with high-corruption-risk individuals and companies that might have a record of previously engaging in corrupt activities or have connections to government officials (SEC and DOJ 2012). Prior involvement by a third party in corruption would almost certainly impede transactions with a firm subject to the FCPA.<sup>4</sup> Given extraction firms are major purchasers

---

<sup>4</sup> Firms subject to the FCPA frequently rely on watch lists of high-corruption-risk individuals and companies when operating in high-corruption risk countries. Reasons to end up on such lists include indications that the party has previously engaged in corrupt activities or has connections to government officials that are thought to be corruptible. The costs of lost business associated with being on a watch list could be substantial to local firms operating in an area where a large proportion of potential customers are subject to the FCPA.

of local services and materials in the communities around them, the indirect effects of the FCPA on local businesses could be significant.

These characteristics of our setting (i.e., natural resource extraction in Africa) suggest that foreign corruption regulation could significantly reduce corruption, both among foreign multinational firms operating in high-corruption-risk areas and among local firms hoping to do business with these firms. Corruption can attenuate the natural resource industry's positive impact on economic development by distorting resource allocation and keeping extractive regimes in place (Shleifer and Vishny 1993; Acemoglu and Robinson 2012; Ortiz-Ospina and Roser 2016). By limiting corruption throughout the extraction sector, foreign corruption regulation could help mitigate these negative aspects of resource extraction and increase local communities' benefits from such activities. Alternatively, foreign corruption regulation may simply impose compliance costs on firms or otherwise prevent them from competing against unregulated, less efficient firms, both of which suggest that foreign corruption regulation could decrease investment in the extraction sector and have a negative effect on local economic development. These two opposing effects are not mutually exclusive and which effect dominates is an empirical question.

### **3. Institutional Details and Research Design**

Estimating the impact of foreign corruption regulation on economic development is difficult because corruption is inherently unobservable and reliable, exogenous measures of local economic activity are difficult to obtain. To overcome these challenges, we focus our analysis on a major shock to the costs of engaging in corrupt activities, a mid-2000s increase in US FCPA enforcement, and measure economic activity in a highly geographically localized area using satellite images of nighttime light emissions around natural resource extraction facilities in Africa. In this section, we describe the institutional features of our setting that motivate these research design choices, including how we assign treatment by the FCPA enforcement shock, the units of observation we use to define an extraction area, and how we measure local economic activity.

#### *3.1 Assignment of Treatment — the Mid-2000s Increase in US FCPA Enforcement*

We consider an extraction facility to be treated by the mid-2000s increase in US FCPA enforcement if the facility has an ultimate beneficial owner (of a stake of 20% or more) that is under US jurisdiction and headquartered in an OECD country. In this section, we discuss the rationale for this assignment of treatment.

Although Congress enacted the FCPA in 1977, the law was not widely enforced until the mid-2000s because of a lack of domestic support and limited international cooperation (Martin et al. 2012; Olken and Pande 2012). A confluence of factors, all occurring around 2005, help to explain the timing of the increase in FCPA enforcement, including (i) an expanded legal definition of bribery, (ii) the introduction of deferred and non-prosecution agreements in FCPA cases, (iii) the enactment of the Sarbanes-Oxley Act, and (iv) an increased willingness of many countries to cooperate with the US government after the 9/11 terrorist attacks (Martin et al. 2012; Brewster 2017). Data from the *Stanford Foreign Corrupt Practices Act Clearinghouse* provide evidence of the dramatic mid-2000s increase in FCPA enforcement activity, particularly against extraction firms operating in Africa.<sup>5</sup> From 1977 until 2004, there were 53 FCPA enforcement actions against corporations (fewer than 2 per year); from 2005-2017, there were 284 cases (more than 20 per year). For non-US firms, the increase in enforcement was even more pronounced, growing from 4 enforcement actions between 1977 and 2005 to 97 cases from 2005 to 2017. Of the 284 total cases between 2005 and 2017, 70 included FCPA violations in Africa (nearly 25%), and 41 of these 70 cases (nearly 60%) were against firms in the natural resource extraction industry.

The FCPA's jurisdictional scope is expansive and cases can be brought by either the SEC and/or the DOJ against US- and non-US-domiciled issuers, domestic concerns, and firms acting in US territory. However, effective prosecution of non-US firms requires cooperation with foreign regulators. Likely for this reason, FCPA enforcement against non-US firms has been limited to firms headquartered in countries that have signed the legally binding *Convention on Combating Bribery of Foreign Public Officials in International Business Transactions* (i.e., the Anti-Bribery Convention). The Anti-Bribery Convention requires cooperation among signatory countries and has been signed by all OECD members and 6 non-members (as of the end of our sample in 2013)—for brevity, we refer to all signatory countries as “OECD countries.”<sup>6</sup> In Figure IA1 of the Internet Appendix, we show that of the 97 non-US firms targeted by an FCPA enforcement action between 2005 and 2017, only two were headquartered in a non-OECD country (Christensen et al. 2020). Although signatory countries have their own foreign corruption regulations, and countries such as Germany and the UK have recently ramped up enforcement, the US dominates the enforcement of

---

<sup>5</sup> For details, see <http://fcpa.stanford.edu/> and Christensen et al. (2020), who also report some of the statistics on FCPA enforcement actions presented in this section.

<sup>6</sup> For a list of countries that signed the OECD Anti-Bribery Convention, see Internet Appendix Table IA1.

foreign corruption regulation, accounting for 83% of all sanctions against legal entities from 1999 to 2018 (OECD 2019).

We classify an extraction facility as being under US jurisdiction if at least one of the facility’s corporate beneficial owners has a stake of more than 20% and is: 1) headquartered in the US, 2) has an SEC-registered cross-listing on a US stock exchange, or 3) discloses an operating segment in the US.<sup>7</sup> A 20% ownership stake generally provides the owner with significant influence, which is an important factor in determining culpability under the FCPA (SEC and DOJ 2012). We obtain information on the identity, ownership stakes, and headquarter countries of the ultimate owners of extraction sites from the *SNL* and *Enverus* databases. We collect data on US cross-listings from the websites of the major depository banks (Bank of New York and Citibank) and data on US reporting segments from *Worldscope*. We verify that a cross-listed firm is an SEC registrant through a search of 20-F and 40-F filings in the *SeekEdgar* database.

Because enforcement of the FCPA has, in practice, been limited to firms headquartered in countries that have signed the Anti-Bribery Convention, we consider only owners that are under US jurisdiction and are also headquartered in an OECD country as being subject to the FCPA (i.e., as treated). To avoid the possibility that our estimates reflect endogenous variation in ownership, we base our treatment assignment on data from 2004 and consider extraction facilities subject to the FCPA in 2004 to always be subject to the FCPA. About 16% of all extraction sites have at least one beneficial owner with significant influence that is subject to the FCPA (see Table 1). The location of extraction facilities owned by a company subject to the FCPA is fairly dispersed across Africa (see Figure 1).

### 3.2 Unit of Observation — Defining an Extractive Area

Our unit of observation is the circular geographic area around an active extraction site (henceforth, a “cell”). In our empirical analyses, we consider cells with radii of between 10 to 100 kilometers. We collect mine-level data from *SNL* and oil-well data from *Enverus*. Both databases provide the latitude and longitude of extraction sites, which enables us to match these data to a particular cell. This high degree of spatial resolution allows us to assess the impact of foreign

---

<sup>7</sup> Under international accounting standards, if a firm has a significant operational and managerial presence in another country, the firm must publicly disclose disaggregated financial information for operations in that country. For foreign firms that disclose a US segment, it is more likely that, if the firm commits an FCPA violation, that action will fall under US jurisdiction.

corruption regulation at a highly geographically localized level, where (as we discuss in Section 2) extraction activities are likely to have a significant direct impact on economic conditions.

Table 1 reports the distribution of extraction facilities across resource types. Our sample includes facilities that extract 19 different commodities, with the largest concentration in gold (24%), followed by coal (14%), and oil (14%). We map the geographic distribution of commodities in Figure 2. As expected, individual resource types cluster geographically, but none of the five major African geographic regions contains fewer than 8 different minerals. To avoid treatment spillovers across wells within a given oil block, we drop blocks that are operated by multiple firms.<sup>8,9</sup> If more than one mineral is extracted on the same site, that cell appears in the dataset as a separate observation for each mineral.<sup>10</sup> We drop inactive mines and oil wells, as well as offshore wells.<sup>11</sup> In Internet Appendix Table IA2, we provide a breakdown of the number of observations affected by our sample restrictions. Overall, our analysis sample contains 478 mines of 19 minerals (624 mine-mineral pairs) and 99 oil wells located across 34 African countries.

### 3.3 *Measuring Local Economic Activity — Nighttime Luminosity*

We measure economic development based on the density of nighttime light emissions (i.e., luminosity). GDP estimates based on national accounts and other common proxies for economic development are often measured with significant error in developing countries (Johnson et al. 2009) and are generally only available at the national level. In contrast, luminosity estimates are available at a far greater degree of geographic specificity and allow for accurately estimating changes in economic growth at the subnational level (Henderson et al. 2011; Henderson et al. 2012; Michalopoulos and Papaioannou 2014). Compared to other measures of economic development (e.g., GDP), luminosity reflects the level of economic activity more broadly. If the benefits of an increase in economic growth are highly concentrated, it is unlikely to significantly

---

<sup>8</sup> Blocks are specific geographic areas in host countries where firms with licenses can drill for oil. Host governments can award different portions of the same block to different firms, particularly if the block is large.

<sup>9</sup> In Internet Appendix Table IA3 and Figure IA2, we assess extent of treatment spillovers across extraction sites in close geographic proximity. Consistent with spillovers introducing measurement error and biasing our estimates towards zero, our results are slightly stronger excluding extraction areas that overlap within a 10-kilometer radius.

<sup>10</sup> 16% of the mines in our sample (77 out of 478 mines) produce more than one mineral. In Figure IA3 and Table IA4 of the Internet Appendix, we find that our results are similar if, for each mine, we only keep the mineral with the highest production value in USD.

<sup>11</sup> In Internet Appendix Figure IA4 and Table IA5, we find that our results remain similar when we include inactive mines (i.e., those with zero reported production in all years of our sample).

impact the level of luminosity. Thus, the level of luminosity is more indicative of the overall well-being of people throughout the community.

We collect luminosity data from the *United States Air Force Defense Meteorological Satellite Program (DMSP)*. DMSP satellites collect data on low-light imaging for every location on the planet every night. The National Geophysical Data Center (NGDC) processes these data (e.g., by removing intense sources of natural light and observations where cloud cover obscures the earth's surface) and distributes the final, annualized data to the public. To operationalize the luminosity data, we compute the cloud-free-observation-weighted average over all stable nightlight pixels for each cell.

Table 3 reports descriptive statistics. The sample consists of 10,122 cell-year observations from 2000 to 2013.<sup>12</sup> *Luminosity* values range from 0 (no light) to 63 (a highly developed urban area). Average *Luminosity* within 10 kilometers of an extraction site is 7.7. *Luminosity* monotonically decreases as we increase the radius around extraction sites.

#### 4. Evidence on the Effect of Foreign Corruption Regulation on Economic Development

To examine the association between foreign corruption regulation and economic development, we estimate how nighttime light emissions change around the 2005 increase in US FCPA enforcement in geographic cells with radii ranging from 10 to 100 kilometers around natural resource extraction facilities. Our generalized difference-in-differences design compares luminosity in cells where one of the extraction site's controlling owners is subject to the FCPA compared to cells where the extraction site does not have an owner subject to the FCPA. Because economic activity likely responds gradually, we map out the yearly coefficient estimates of the treatment effect based on the following OLS regression:

$$\ln(Luminosity_{c,t} + 0.01) = \beta_1 FCR_t \times Year_t + Fixed\ Effects + \varepsilon_{c,t} \quad (1)$$

$\ln(Luminosity + 0.01)$  is the natural logarithm of the average luminosity in cell  $c$  and year  $t$  plus 0.01.<sup>13</sup>  $FCR$  is an indicator equal to one if, in 2004, at least one extraction site owner (of 20% or more) is subject to the FCPA (i.e., is under US jurisdiction and headquartered in an OECD country).  $Year$  is a set of indicators for each year of our sample period. We omit the indicator for

<sup>12</sup> In 2014, the NGDC changed its processing method for the luminosity data.

<sup>13</sup> The absence of reported nighttime luminosity does not necessarily imply an absence of economic activity (Hodler and Raschky 2014). Following Michalopoulos and Papaioannou (2013) and Hodler and Raschky (2014), we define our dependent variable as the natural logarithm of *Luminosity* plus 0.01 so as to include observations with a value of zero and to account for skewness in the variable's distribution. We find similar results when we alternatively use  $\ln(Luminosity)$  as the dependent variable (see Figures IA5 and IA6 of the Internet Appendix).

2004, which serves as the benchmark period. We include extraction-site-by-commodity fixed effects ( $Property \times Commodity$ ) to control for differences in luminosity arising from time-invariant (or slow-moving) factors that are specific to each extraction site (e.g., geological conditions, property size). We add  $Commodity \times Year$  fixed effects to account for commodity-specific time trends. We test for statistical significance using Conley (1999) standard errors, which correct for spatial correlation within a 500-km radius and infinite serial correlation.

In Figure 3 Panel A, we graph the yearly  $FCR \times Year$  coefficient estimates and their corresponding 95% confidence intervals. In support of the parallel-trends assumption, treated and control cells have similar trends in luminosity before 2005. Consistent with foreign corruption regulation increasing economic activity, between 2005 and 2009, treated cells exhibit a gradually increasing level of luminosity relative to control cells. After 2008, the treatment effect stabilizes at an approximately 50% higher level. In interpreting the economic significance, it is important to note that in this specification we focus on the area in the immediate vicinity (i.e., a 10-kilometer radius) around the extraction sites, where the extraction industry employs an estimated 18% of the cell's workforce.

To estimate the average effect in the post-2004 period and to simplify the reporting of sensitivity tests, we also present results based on a specification where we replace the individual *Year* indicators with a single *Post 2004* indicator, which takes the value of one for all years after 2004. Table 4 reports the corresponding regression results. In Column (1), the  $FCR \times Post\ 2004$  coefficient estimate is positive and statistically significant, indicating that the cells surrounding extraction facilities subject to FCPA enforcement exhibit an increase in economic activity of approximately 40% relative to areas that are not.<sup>14</sup>

If the observed increase in luminosity is attributable to changes in the extraction sector, we expect the size of the observed effect to diminish as the area of the cell increases and the facility becomes a less central part of economic activity within a particular cell. To examine how the effect diffuses geographically, we re-estimate the regression for increasingly larger cells around the extraction site. In Figure 3 Panel B, we graph the  $FCR \times Post\ 2004$  coefficient estimates and their

---

<sup>14</sup> To examine whether the observed increase in economic activity is concentrated among facilities extracting particular commodity types, in Internet Appendix Table IA6 we re-estimate Eq. (1) dropping each commodity one by one. We find that our results are robust to the individual exclusion of each commodity, except for gold, which contributes 24% of our sample observations. However, as shown in Internet Appendix Figure IA7, the pattern of the treatment effect over time excluding gold mines is similar to that for the main analysis in Figure 3 Panel A.



corresponding 95% confidence intervals for cells with radii of 10, 25, 50, 75, and 100 kilometers. The impact of foreign corruption regulation on luminosity decreases monotonically in the length of the radius of the cell, suggesting that the increase in economic activity is attributable to changes in the extraction sector. The point estimates are positive for all radii, but statistically significant (at least at the 10% level) only up to a distance of 50 kilometers. At a 50-kilometer radius, the coefficient on  $FCR \times Post\ 2004$  implies an increase in luminosity of approximately 8%. Our 50-kilometer radius specification is comparable to the size of the geographical area used in Mamo et al. (2019), where the authors document a 74% increase in luminosity when a new mine opens in a given region (see Mamo et al. 2019 Table 3 Column 4).

In Table 4 Columns (2) to (4) we present the results of three sensitivity tests. First, because the activity of resource extraction itself produces light emissions, to ensure that we capture the economic activity in the communities surrounding the extraction sites rather than at the extraction site itself, we exclude the 1-kilometer-radius cell that surrounds the extraction site. In Table 4 Column (2), we find that the estimated treatment effect remains positive, statistically significant, and only slightly attenuates when we re-estimate our baseline model on the donut-shaped 1-10 km area around the extraction site (coefficient estimate of 0.320 compared to 0.338 in Column 1).

Second, in Table 4 Column (3), we include region-specific time trends (i.e.,  $Region \times Year$  fixed effects) to account for time-varying institutional and political factors (e.g., climate conditions, armed conflicts) that are correlated with Africa’s five main geographic regions (shown in Figures 1 and 2). The estimated treatment effect attenuates from 0.338 to 0.301, but remains statistically significant. We do not include  $Country \times Year$  fixed effects because the geographical clustering of minerals (see Figure 2) would severely limit the number of observations that contribute to the identification of the  $FCR \times Post\ 2004$  coefficient estimate.

Third, to corroborate the role of foreign corruption regulation in the observed increase in local economic activity, in Table 4 Column (4), we perform a falsification test using extraction facilities owned by firms under US jurisdiction that are headquartered in *non-OECD* countries as our pseudo-treatment group. As discussed in Section 3, FCPA enforcement actions are essentially limited to firms headquartered in countries that signed the OECD’s Anti-Bribery Convention. So, firms under US jurisdiction from non-OECD countries likely experience less of an enforcement shock. The advantage of this test is that non-OECD firms under US jurisdiction are likely more similar (at least along some dimensions) to our treated firms than non-US-jurisdiction firms. If the

observed changes in luminosity are attributable to an unobservable factor besides foreign corruption regulation, we would expect to observe similar effects for these firms. We exclude from the analysis cells with facilities owned by firms under US jurisdiction and headquartered in OECD countries (i.e., the treated firms in the main analysis). Consistent with the increase in economic activity in cells with extraction facilities subject to the FCPA being attributable to foreign corruption regulation, we find no evidence of a significant change in luminosity in areas where an extraction facility's owner is under US jurisdiction but *not* headquartered in an OECD country (and thus not subject to the FCPA).<sup>15</sup> A plot of the treatment effect coefficients from this analysis over time in Internet Appendix Figure IA8 provides further support for this conclusion.

Overall, the evidence in this section indicates that local economic activity is higher in the areas around extraction facilities with owners subject to foreign corruption regulation, suggesting that the regulation's corruption reducing effects outweigh the opposing effects of any reduction in economically beneficial investment arising from compliance costs.

## 5. Effect of Foreign Corruption Regulation on Corruption Perceptions

If corruption in the extraction sector negatively affects economic development, the observed increase in local economic activity following the increase in FCPA enforcement could be explained (in part) by a reduction in corruption. Yet, measuring corruption directly is difficult given the incentives of both the bribe payer and receiver to conceal their corrupt activities. As an alternative (and empirically feasible) approach, we measure corruption using survey data on local residents' *perceptions* of corruption. An issue with this approach is that perceptions are subjective and influenced by individual characteristics and biases, and thus might not accurately reflect the true extent of corruption. Yet, in terms of stimulating economic activity, which requires a degree of trust among participants (Guiso et al. 2009), residents' perceptions of corruption could be as important as (or even more important than) the underlying level of corruption. If the observed increase in economic activity in areas with extraction facilities subject to the FCPA is attributable to a reduction in corruption, we expect perceived corruption in those areas to decline after 2004.

We collect sub-nationally geocoded data on perceptions of corruption from the Afrobarometer survey. Afrobarometer, a non-partisan research institution, regularly conducts

---

<sup>15</sup> Based on the coefficient estimates, we can say with 95% certainty that the increase in luminosity in cells where the extraction facility is under US jurisdiction, but not subject to the OECD Anti-Bribery Convention, does not exceed 21%. The analysis in Section 6 allows us to provide a more precise estimate of the effect.

public opinion surveys in more than 30 African countries. The Afrobarometer survey provides data at the individual level in highly localized areas. A drawback is that the survey does not follow an individual or local area through time (i.e., each survey round includes a new set of respondents and villages/towns). We use data from rounds one to six of the Afrobarometer survey, a period that stretches from 1999 to 2015 and measure perceived corruption using the answers to the survey question “How many of the following people do you think are involved in corruption: Government officials?” We define an indicator, *Corrupt Government*, equal to one if an individual’s response to the question is “most of them” or “all of them.”

The Afrobarometer also surveys individuals’ satisfaction with the local government. If, in the presence of foreign corruption regulation, public officials can less easily extract bribes, they may be less inclined to prioritize extraction firms over other more socially beneficial sectors of the economy. Residents are likely to be more satisfied with a local government that is responsive to the demands of its citizens. We examine whether people living near an extraction facility subject to the FCPA are more satisfied with their local government using the answers to the following survey question: “Do you approve or disapprove of the way the following people have performed their jobs over the past twelve months: Local government/official/assembly?” We define an indicator, *Satisfaction with Local Government*, equal to one if an individual responds “approve” or “strongly approve”. The correlation between *Corrupt Government* and *Satisfaction with Local Government* is -0.16, suggesting that the two measures capture related but independent constructs.

We restrict the sample to survey respondents who live within 100 kilometers of an extraction facility. Our final sample covers the survey responses of 57,629 African citizens in 4,535 localities across 31 African countries between 1999 and 2015. In Internet Appendix Table IA7, we provide a breakdown of the number of respondent observations by country and survey round. Table 5 Panel A reports descriptive statistics. Approximately 17% of survey participants live in close proximity to an extraction site whose owner is subject to the FCPA. 44% of individuals perceive the government to be highly corrupt and 52% are satisfied with their local government. Roughly three quarters of our survey responses were collected after 2004. 49% of respondents are female, 44% live in urban areas, and their average age is 37 years old.

To examine how foreign corruption regulation affects perceptions of corruption and satisfaction with the local government, we estimate the following OLS regression:

$$Perception_{i,t} = \beta_1 FCR Exposure_i \times Post\ 2004_t + Controls_i + Fixed\ Effects + \varepsilon_{i,t} \quad (2)$$

*Perception* is either *Corrupt Government* or *Satisfaction with Local Government* (as defined above) for individual  $i$  in year  $t$ . *FCR Exposure* is an indicator equal to one if the closest extraction facility within 100 km of survey respondent  $i$  is subject to the FCPA. *Post 2004* is an indicator for years after 2004. We include controls for several individual characteristics that could be associated with perceptions, including: gender (*Female*), because perceptions systematically differ across genders (e.g., Croson and Gneezy 2009; Melgar et al. 2010; D’Acunto 2020); *Urban* because individuals living in cities might interact with government officials and observe corrupt activities more frequently (Hunt 2004; Mocan 2004); and age ( $\ln(\text{Age})$ ) to account for inter-generational differences in corruption perceptions (Torgler and Valev 2006). We include *Region*  $\times$  *Year* fixed effects to account for time-varying political factors (e.g., corruptions scandals) that are correlated with Africa’s five main geographic regions and add *Mineral* fixed effects to control for time-invariant or (slow-moving) differences in corruption perceptions across areas that extract different minerals.<sup>16</sup> We cluster standard errors at the village level because individuals’ perceptions are likely correlated within localities.

In Table 5 Panel B, we report the regression results from estimating Equation (2). In Column (1), the *FCR*  $\times$  *Post 2004* coefficient estimate is negative, statistically significant, and indicates that individuals living near extraction sites whose owners are subject to foreign corruption regulation are 8% less likely to perceive their government as corrupt after 2004 (-0.044/0.548). In Column (2), we include control variables and find that the estimated coefficient magnitude for *Corrupt Government* remains virtually unchanged. The coefficients on the controls are all statistically significant. Women and older individuals have lower corruption perceptions whereas urban residents perceive their government to be more corrupt. The fact that including these control variables has little effect on the *FCR*  $\times$  *Post 2004* coefficient estimate suggests that differences in survey respondent characteristics across treatment and control areas are unlikely to explain our findings.<sup>17</sup>

In Figure 4 Panel A, we plot the treatment effect over time based on the timing of each Afrobarometer survey round. In support of the parallel-trends assumption, there is no visible

---

<sup>16</sup> We do not include individual survey respondent or geographic area fixed effects in Equation (2) because Afrobarometer typically interviews different people in different locations in each survey round.

<sup>17</sup> In Internet Appendix Table IA8, we report consistent results excluding responses from round one of the Afrobarometer survey, which were compiled from several independent research efforts, and are thus not directly comparable to the other survey rounds (Bauer and Beard 2004).

difference in the pre-treatment trends in corruption perceptions for areas subject to foreign corruption regulation and those that are not. In the post-2004 period, the treatment effect is negative for all periods and particularly strong in the period immediately following the increase in FCPA enforcement (i.e., round R3 in 2005/2006). That the estimated treatment effect is largest in the period immediately after the enforcement increase and then subsequently declines is consistent with, over time, respondents benchmarking their perceptions against the “new normal” of a less corrupt environment.

In Table 5 Panel B Columns (3) and (4), we examine changes in individuals’ satisfaction with their local government. We find that, after the 2004 FCPA enforcement increase, residents of extraction areas subject to the regulation are approximately 18% more likely to be content with the performance of their local government. In Figure 4 Panel B, we map out the treatment effect over time and find no evidence of differing pre-period trends between the treatment and control groups. In the post-period, the treatment effect is positive for all periods and, once again, strongest immediately after the enforcement increase.

Overall, the analyses in this section suggest that a reduction in corruption is a potential explanation for the observed increase in economic activity around treated extraction areas following the post-2004 increase in FCPA enforcement.

## **6. Changes in the Extractive Sector**

Next, we explore changes to activities in the extraction sector that could explain why perceived corruption declines and economic activity increases with stricter enforcement of foreign corruption regulation. Several non-mutually-exclusive possibilities exist, including a shift in resources away from the extraction sector, changes in the activities of existing firms, and less corrupt firms entering the sector.

### *6.1 Resources Allocated to the Extraction Sector*

Prior research finds that foreign corruption regulation is associated with lower investment in high-corruption-risk areas (e.g., Beck et al. 1991; Hines 1995; Cuervo-Cazurra 2006; Christensen et al. 2020), suggesting that the positive association between foreign corruption regulation and local economic development could be explained by a decrease in activity in the corruption-prone extraction sector. For instance, the opportunity to obtain bribes can incentivize government officials to allow extraction firms to produce at levels that exceed what is optimal for the local economy. Foreign corruption regulation, by reducing the availability of bribes, decreases

the incentives of officials to permit overproduction, and thereby could lead to a shift in resources away from the extraction sector. Such an effect would reduce the extraction sector's direct contribution to local economic growth, but could allow other sectors (e.g., agriculture) to thrive, potentially increasing the overall level of development.

In the Internet Appendix, we examine changes in two measures of activity in the extraction sector—facility-level employment (Table IA9 and Figure IA9) and production (Table IA10 and Figure IA10). Unfortunately, both analyses are constrained by data limitations. First, we are forced to limit our sample to mines because, for oil wells, we cannot observe production prior to 2007 or employment at the facility level. Second, production data at the mine level are unavailable for many firms and Afrobarometer does not ask survey questions about mining-related employment after 2006. Nonetheless, inconsistent with the increase in development being explained by a decline in activity in the extraction sector, results from these analyses provide no evidence that production or employment levels declined after the 2004 increase in FCPA enforcement.

## 6.2 *Extractive Firms' Business Practices*

Economic development could also increase if more of the expenditures made by firms affiliated with the extraction sector reach their most efficient uses and provide more benefits to the local community. One way this could occur is if firms adopt business practices that are more beneficial to the local communities where they operate. For example, in a case study of a large foreign-owned Peruvian gold mining firm, Argon and Rud (2013) find that the existence of strong backward linkages between mining firms and local communities, enabled by a corporate policy aimed at increasing the participation of local firms and workers, led to a more positive association between natural resource extraction and local income growth.

To substantiate whether the observed increase in economic development is, at least partly, attributable to a change in firms' business practices, we examine whether the association between the level of resource production and local economic activity increases when extraction firms are subject to foreign corruption regulation. Examining changes in the association between production and economic activity is complicated by two concerns. First, production decisions are endogenous. For instance, if economic conditions in an area improve (e.g., because of business development unrelated to natural resources), resource extraction could become more profitable and production quantities could increase. Second, because not all firms report production at the facility-level, production data are limited to a subset of facilities.

To mitigate these concerns, we use variation in the world prices of the individual commodities produced by the facilities in our sample as an instrument for production quantities. Our approach is based on the idea that production levels should increase as the world commodity price increases (and vice versa). Fluctuations in world commodity prices are plausibly exogenous to the production decisions of individual facilities (i.e., individual extraction sites are too small to affect global commodity markets), and thus likely satisfy the exclusion restriction (below we provide evidence that world commodity prices also satisfy the relevance criterion). Using world prices as an instrument also has the advantage that it does not restrict our sample (Dube and Vargas 2013; Berman et al. 2017). A potential concern with this approach is that changes in commodity prices are highly correlated, limiting the variability of the instrument. However, as shown in a plot of the price paths of our 19 sample commodities (Figure IA11), there is significant variation in world prices across commodities over time, particularly after 2004.

Conditioning the association between foreign corruption regulation and economic activity on an exogenous shock to production also alleviates some potential identification concerns. In our analysis of changes in economic activity around the post-2004 increase in FCPA enforcement (see Section 4), the main threat to identification is the non-random location of treated and non-treated facilities. Any determinants of this non-random assignment correlated with the 2005 increase in FCPA enforcement could present an alternative explanation for the results in Section 4. For instance, if the firms subject to foreign corruption regulation tend to operate in areas to which their headquarter country has close economic connections, any factor correlated with that economic connection that changes around 2005 (e.g., trade agreements, headquarter-country growth, or development aid) represents a potential correlated omitted variable. The narrower focus on how extraction activity maps into local economic development alleviates concerns about omitted variables that are uncorrelated with changes in world commodity prices.

We collect mineral prices from the US Geological Survey and the World Bank Commodities database. We exclude coal, for which there is no uniform global price.

#### 6.2.1 *The Relevance of World Commodity Prices as an Instrument*

We assess the relevance of the price instrument by examining the association between commodity prices and resource production at the facility level (for the subset of facilities that report production quantities) in the following OLS regression:

$$\ln(\text{Production}_{c,t} + 0.01) = \beta_l \ln(\text{Price}_{m,t}) + \text{Fixed Effects} + \varepsilon_{c,t} \quad (3)$$

*Production* is the production value (calculated using commodity prices from the year 2000) for the facility in cell  $c$  in year  $t$ . *Price* is the average world price for commodity  $m$  in year  $t$ . We include *Property*×*Commodity* and *Year* fixed effects and test for statistical significance using Conley (1999) standard errors corrected for spatial correlation within a 500-km radius.

Table 6 Panel A Column (1) reports the results. The coefficient estimate on  $\ln(\text{Price})$  is positive and statistically significant, indicating that facilities produce more when world commodity prices are higher. The coefficient magnitude, which can be interpreted as an elasticity, implies that a 1-percent increase in commodity prices is associated with a 1.045 percent increase in production. This elasticity decreases to 0.989 when we additionally control for region-specific time trends in Column (2). Overall, the results in Table 6 Panel A support that world commodity prices are a relevant instrument for extraction activities.

### 6.2.2 The Unconditional Association between Commodity Prices and Luminosity

To provide a benchmark for how natural resource extraction affects economic activity, we examine the unconditional association between world commodity prices and luminosity in the following OLS regression model:

$$\ln(\text{Luminosity}_{c,t} + 0.01) = \beta_1 \ln(\text{Price}_m) + \text{Fixed Effects} + \varepsilon_{c,t} \quad (4)$$

All variables are measured as previously defined and the fixed effects are the same as in Eq. (1).

Figure 5 graphs the  $\beta_1$  coefficient estimates and associated 95% confidence intervals for cells with radii of 10, 25, 50, 75, and 100 kilometers. The association between luminosity and world commodity prices is positive for all radii and statistically significant (at least at the 10% level) for the radii from 10 to 75 kilometers when we include *Property*×*Commodity* and *Year* fixed effects and for all reported radii when we replace *Year* with *Region* × *Year* fixed effects. At 10 kilometers, the  $\beta_1$  coefficient estimate implies an elasticity of luminosity to world commodity prices of approximately 0.20. Consistent with the increase in luminosity being attributable to the extraction facility, regardless of the fixed effect structure, the association between luminosity and resource prices monotonically declines in the radius of the cell.<sup>18</sup>

---

<sup>18</sup> Consistent with the evidence in Mamo et al. (2019), the positive association between resource extraction and luminosity also provides evidence against a strong form of the resource curse in Africa—although it does not preclude a less extreme version of the resource curse whereby the positive economic impact of resource extraction is less than what it would have been in the absence of corruption.



### 6.2.3 Foreign Corruption Regulation and the Contribution of Resource Extraction to Development

To examine how foreign corruption regulation affects the relationship between resource extraction and economic activity, we estimate the following regression:

$$\begin{aligned} \ln(0.01 + \text{Luminosity}_{c,t}) = & \beta_1 \text{FCR}_i \times \text{Year}_t \times \ln(\text{Price}_m) \\ & + \beta_2 \text{FCR}_i \times \text{Year}_t + \text{Fixed Effects} + \varepsilon_{c,t} \end{aligned} \quad (5)$$

Similar to Eq. (1), we first estimate the treatment effect by year. As in Eq. (1), we include *Property*×*Commodity* and *Commodity*×*Year* fixed effects. In addition, we include *FCR*×*Year* fixed effects to control for time-trends in luminosity that differ between areas where facilities are subject to corruption regulation and those that are not. We test for statistical significance using Conley (1999) standard errors corrected for spatial correlation within a 500-km radius.

Figure 6 Panel A graphs the results from estimating Eq. (5). The estimated counter-factual treatment effects in the pre-treatment period are close to zero and statistically indistinguishable from the benchmark period. In the post-period, variation in resource production in treated cells, as captured by changes in world commodity prices, exhibits an increasing association with luminosity relative to control cells. The gradual increase in the coefficient estimate is consistent with changes in firm activities taking time to materialize. After 2008, the treatment effect stabilizes at an increase in the elasticity between luminosity and commodity prices of around 0.08—an approximately 40% increase relative to the unconditional association between luminosity and commodity prices in a 10-kilometer radius, reported in Figure 5.

In Table 6 Panel B, we quantify the magnitude of the average increase in extraction activities' contribution to economic growth over the entire post-2004 period and report several robustness tests. The baseline results reported in Column (1) suggest that, in the pre-period, the effect of extraction activities on economic growth is higher in areas with a facility subject to foreign corruption regulation relative to areas that are not, but the difference is not statistically significant (the *FCR*×*Ln(Price)* coefficient is 0.158). More importantly, the estimated treatment effect of foreign corruption regulation in the post-period, *FCR*×*Post 2004*×*Ln(Price)*, is 0.070 and statistically significant. The magnitude of the coefficient estimate implies a 37% increase relative to the unconditional association between luminosity and commodity prices in the 10-kilometer radius reported in Figure 5.

In Figure 6 Panel B, we graph the *FCR*×*Post 2004*×*Ln(Price)* coefficient estimates and their corresponding 95% confidence intervals for cells with radii of 10, 25, 50, 75, and 100

kilometers. We find that the impact of foreign corruption regulation on the association between production and luminosity decreases monotonically in the size of the radius around the extraction sites. The point estimates are positive for all radii but statistically significant (at least at the 10% level) up to a radius of 75 kilometers. At 75-kilometers, the  $FCR \times Post\ 2004 \times Ln(Price)$  coefficient implies an increase in the elasticity of luminosity to world commodity prices of 0.02.

In Table 6 Panel B Columns (2) to (4), we present the results of the same three sensitivity tests we report for Eq. (1) in Table 4. First, we find results almost identical to the baseline model when we estimate our triple-difference model on the donut-shaped 1-10 km area around the extraction site (coefficient of 0.073 compared to 0.070 in Column 1). Second, when we control for time-varying factors that are correlated with Africa's five regions in Column (3), the estimated treatment effect attenuates from 0.070 to 0.054 and becomes statistically insignificant (p-value of 0.106). However, in Figure IA12 of the Internet Appendix, we show that the event-time pattern of the treatment effect remains very similar to the baseline model (Figure 6 Panel A), inconsistent with time-varying regional characteristics driving our results. Third, in Column (4), when we exclude treated extraction sites from the sample and counterfactually classify extraction facilities under US jurisdiction but not headquartered in an OECD country as treated, we find a statistically insignificant decrease in the association between extraction activities and luminosity. With 95% certainty, the increase in the contribution of resource production to economic activity in cells where extraction facilities are under US jurisdiction but not subject to the OECD Anti-Bribery Convention does not exceed 2.9%.

Overall, the evidence in this section suggests that the contribution of extraction firms to local economic activity is higher in the presence of foreign corruption regulation.

### 6.3 *New Firms Entering the Extraction Sector*

In this section, we examine whether changes in ownership can explain the increase in extraction firms' contribution to local economic development. Within the extraction industry, corruption provides an incentive for officials to allocate permits to the firms that pay the largest bribes, rather than the most efficient firms (e.g., Hsieh and Klenow 2009). If foreign corruption regulation reduces the supply of bribes, and local officials no longer have an incentive to misallocate permits, more productive firms might start operating extraction sites. Because the new firms can extract commodities at a lower marginal cost (i.e., they are more productive), they can produce more output and need to source more local supplies and workers, resulting in increased

economic activity. Foreign corruption regulation could similarly increase development if compliance costs force foreign firms to sell to more (locally) productive competitors (e.g., domestic firms) not subject to the regulation.

To assess whether the selection of more productive firms drives the observed increase in economic activity, we examine changes in luminosity around mine ownership changes in the post-2004 period by estimating the following two OLS regressions:

$$\begin{aligned} \ln(\text{Luminosity}_{c,t} + 0.01) = & \sum_t \beta_1 \text{Year Relative to Ownership Change}_{c,t} \\ & + \text{Fixed Effects} + \varepsilon_{c,t} \end{aligned} \quad (6)$$

$$\begin{aligned} \ln(\text{Luminosity}_{c,t} + 0.01) = & \sum_t \beta_1 \text{Year Relative to Ownership Change}_{c,t} \times \ln(\text{Price}_{m,t}) \\ & + \text{Fixed Effects} + \varepsilon_{c,t} \end{aligned} \quad (7)$$

In Eq. (6), we examine changes in luminosity (without using world commodity prices as an instrument) and in Eq. (7) we examine extraction activities' contribution to economic activity (by exploiting variation in commodity prices as an instrument for resource production). *Year Relative to Ownership Change* is a set of event-time indicators for each year relative to the ownership change. The other variables and fixed effects are the same as in Eqs. (1) and (5). We limit our sample to mines because we cannot observe ownership changes at the facility level for oil wells. To be included in our sample, we require a mine experience at least one ownership change after 2004. To simplify the analysis, we further limit the sample to extraction facilities that are subject to the FCPA, which is why *FCR* is not included in the regressions.

In Figure 7 Panel A, we plot the *Year Relative to Ownership Change* coefficient estimates. The pattern is inconsistent with the entry of new, more productive firms explaining why economic activity is higher in the presence of foreign corruption regulation. The figure shows that increases in luminosity are concentrated in the years *prior* to an ownership change. After an ownership change, luminosity gradually decreases relative to the benchmark year, *t-1*. In Figure 7 Panel B, we find a similar pattern.

Overall, the results in this section suggest that the increase in extraction firms' contribution to local economic development following foreign corruption regulation cannot be explained by ownership changes, but rather is more likely attributable to existing extraction firms adopting business practices that are more beneficial to the local communities where they operate.

## 7. Conclusion

Recognizing the disproportionate impact of corruption in developing countries, governments in many developed countries have enacted regulation to curb the bribery of foreign public officials. The most prominent and widely enforced of these anti-corruption regulations is the US FCPA. We examine the impact of a significant increase in FCPA enforcement on economic development in Africa. Measuring local economic activity by nighttime luminosity, we document that, after the increase in FCPA enforcement, economic activity increases by 8% within a radius of 50 kilometers of extraction facilities whose owners are subject to the FCPA. Consistent with a decline in corruption contributing to the increase in economic activity, local perceptions of corruption decline and satisfaction with the local government increases. We find no evidence of a decline in production or employment in the extraction sector. Rather, consistent with the increase in economic activity being driven (at least in part) by extraction firms shifting to business practices that are more beneficial (or less detrimental) to the local communities where they operate, the association between extraction activities and local economic activity increases by 37%.

Our findings suggest that foreign corruption regulation can be an effective policy instrument for changing corporate behavior and that, despite any increase in the costs of operating in high-corruption-risk countries, anti-corruption regulation originating in developed countries can have a positive impact on the economic conditions in developing countries—that is, it can (to some extent) mitigate factors that contribute to the resource curse. This is important because developing countries may not themselves have the institutional strength or political will to address misconduct by multinational corporations. A limitation of our analysis is that we cannot observe microlevel changes in facility-level activities and thus cannot speak to exactly how firms change their behavior (e.g., providing training to local workers or supporting local infrastructure projects) because of foreign corruption regulation.

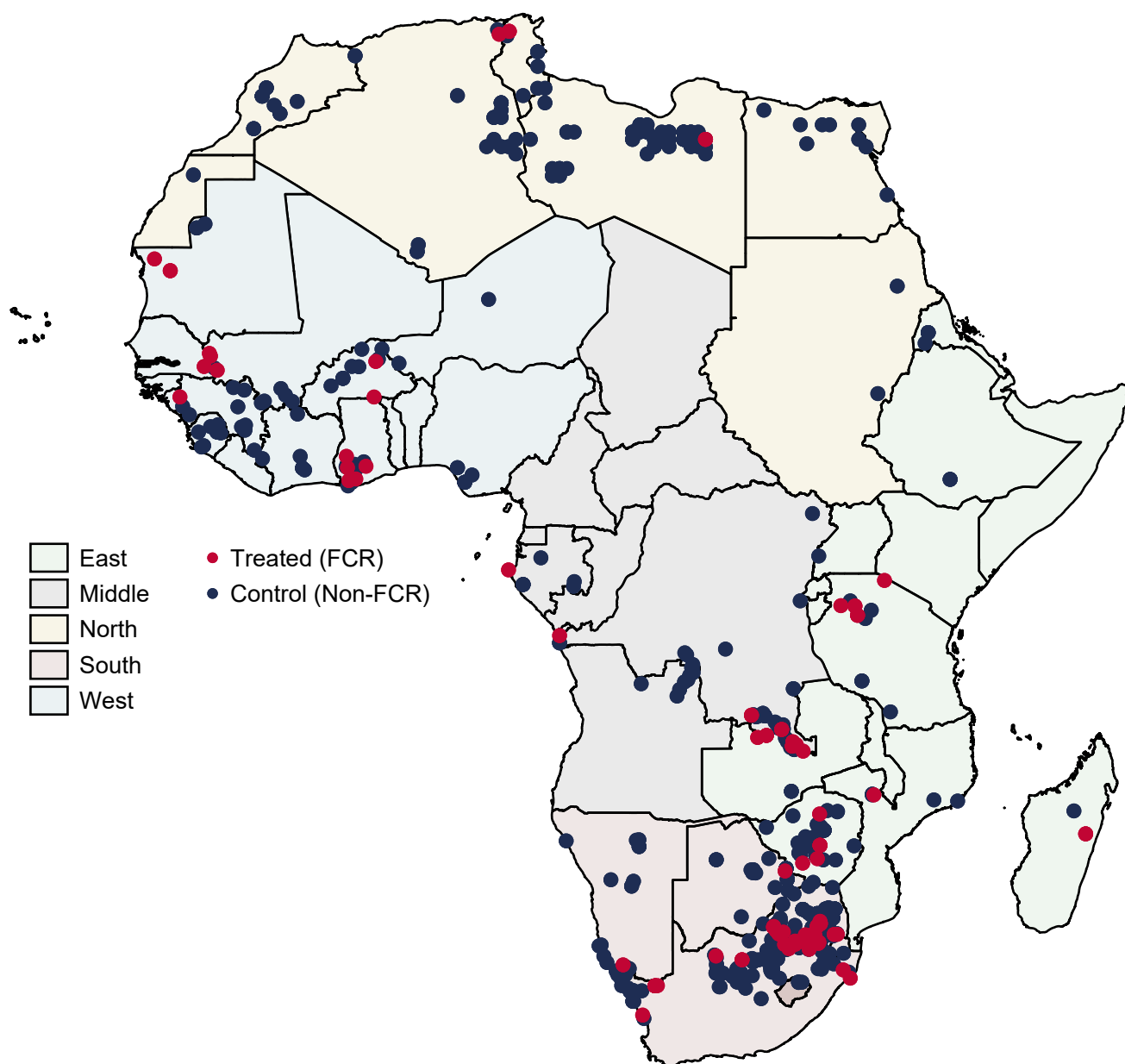
## References

- Acemoglu, D., & Robinson, J. A. (2012). *Why Nations Fail: The Origins of Power, Prosperity and Poverty*. New York: Crown Publishers.
- Aragón, F.M., and Rud, J.P. (2013). “Natural Resources and Local Communities: Evidence from a Peruvian Gold Mine.” *American Economic Journal: Economic Policy*, 5 (2): 1-25.
- Aragón, F.M., and Rud, J.P. (2016). “Polluting Industries and Agricultural Productivity: Evidence from Mining in Ghana.” *Economic Journal*, 126: 1980-2011.
- Auty, R.M. (1993). *Sustaining Development in Mineral Economies: The Resource Curse Thesis*. New York: Routledge.
- Avis, E., Ferraz, C., & Finan, F. (2016). “Do Government Audits Reduce Corruption? Estimating the Impacts of Exposing Corrupt Politicians.” *Journal of Political Economy*, forthcoming.
- Bauer, P., and Beard, V.P. (2004). “Data Codebook for the Twelve-Country Merged Data Set compiled from Round 1 Afrobarometer Surveys in Botswana, Ghana, Lesotho, Malawi, Mali, Namibia, Nigeria, South Africa, Tanzania, Uganda, Zambia and Zimbabwe.” Afrobarometer
- Beck, P. J., Maher, M. W., & Tschoegl, A. E. (1991). “The Impact of the Foreign Corrupt Practices Act on US Exports.” *Managerial & Decision Economics*, 12(4), 295–303.
- BenYishay, A., Rotberg, R., Wells, J., Lv, Z., Goodman, S., Kovacevic, L., Runfolo, D. 2017. Geocoding Afrobarometer Rounds 1–6: Methodology & Data Quality. AidData.
- Berman, N., Couttenier, M., Rohner, D., & Thoenig, M. (2017). “This Mine is Mine! How Minerals Fuel Conflicts in Africa.” *American Economic Review*, 107(6), 1564–1610.
- Bertrand, M., Bombardini, M., Fisman, R., and Trebbi, F. (2020). “Tax-Exempt Lobbying: Corporate Philanthropy as a Tool for Political Influence.” *American Economic Review*, 110 (7): 2065-2102.
- Blundell-Wignall, A., and Roulet, C. (2017). “Foreign Direct Investment, Corruption and the OECD Anti-Bribery Convention.” *OECD Working Papers on International Investment*, 2017/01. Paris: OECD Publishing.
- Bobonis, G. J., Gonzalez-Brenes, M., & Castro, R. (2013). “Public Transfers and Domestic Violence: The Roles of Private Information and Spousal Control.” *American Economic Journal: Economic Policy*, 5(1), 179–205.
- Brewster, R., & Buell, S. W. (2017). “The Market for Global Anticorruption Enforcement.” *Law and Contemporary Problems*, 80(1), 193–214.
- Christensen, H.B., and Maffett, M.G., and Rauter, T. (2020). “Policeman for the World: The Impact of Extraterritorial FCPA Enforcement on Foreign Investment and Internal Controls”. Working Paper.
- Chuhan-Pole, P., Dabalen, A., & Land, B. (2017). *Mining in Africa. Are Local Communities Better Off?* Washington, DC: World Bank.
- Colonnelli, E., & Prem, M. (2020). “Corruption and Firms” Working Paper.
- Conley, T.G. (1999). “GMM Estimation with Cross Sectional Dependence.” *Journal of Econometrics* 92 (1): 1–45.
- Corden, W., & Neary, J. (1982). “Booming Sector and De-Industrialisation in a Small Open Economy.” *The Economic Journal*, 92(368), 825-848.
- Croson, R., and Gneezy, U. (2009). “Gender Differences in Preferences.” *Journal of Economic Literature*, 47 (2): 448-74.
- Cuervo-Cazurra, A. (2006). “Who Cares about Corruption?” *Journal of International Business Studies* 37(6): 803–822.
- Cuervo-Cazurra, A. (2008). “The Effectiveness of Laws against Bribery Abroad.” *Journal of International Business Studies*, 39(4), 634–651.
- D'Acunto, F. (2020). “Identity and Choice Under Risk.” Working Paper.
- D’Souza A. (2012). “The OECD Anti-Bribery Convention: Changing the Currents of Trade.” *Journal of Development Economics* 97: 73–87.
- Deaton, A. (1999). “Commodity Prices and Growth in Africa.” *Journal of Economic Perspectives*, 13 (3):

- Dube, O., & Vargas, J. F. (2013). "Commodity Price Shocks and Civil Conflict: Evidence from Colombia." *Review of Economic Studies*, 80(4), 1384–1421.
- Ferraz, C., & Finan, F. (2008). "Exposing Corrupt Politicians: The Effects of Brazil's Publicly Released Audits on Electoral Outcomes." *Quarterly Journal of Economics*, 123(2), 703–745.
- Graham, J. L. (1984). "The Foreign Corrupt Practice Act: A New Perspective." *Journal of International Business Studies*, 15(3), 107–121.
- Guiso, L., Sapienza, P., & Zingales, L. (2009). Cultural Biases in Economic Exchange. *Quarterly Journal of Economics*, 1095–1131.
- Henderson, J.V., Storeygard, A., & Weil, D.N. (2011). "A Bright Idea for Measuring Economic Growth." *American Economic Review: Papers & Proceedings* 2011, 101:3, 194–199.
- Henderson, J.V., Storeygard, A., & Weil, D.N. (2012). "Measuring Economic Growth from Outer Space." *American Economic Review*, 102 (2), 994–1028.
- Hines, J. Jr. (1995). "Forbidden Payment: Foreign Bribery and American Business after 1977." National Bureau of Economic Research. Working Paper.
- Hodler, R., & Raschky, P. (2014). "Regional Favouritism." *Quarterly Journal of Economics*, 129(2), 995–1033.
- Hsieh, C., & Klenow, P. (2009). "Misallocation and Manufacturing TFP in China and India." *Quarterly Journal of Economics*, 124(4), 1403–1448.
- Humphreys, M., Sachs, J., & Stiglitz, J. E. (2007). *Escaping the Resource Curse*. New York: Columbia University Press.
- Hunt, J. (2004). "Trust and Bribery: The Role of the Quid Pro Quo and the Link with Crime." NBER Working Paper, No. 10510.
- Huskins, P. C. (2008). "FCPA Prosecutions: Liability Trend to Watch." *Stanford Law Review*, 60(5), 1447–1457.
- Johnson, S., Larson, W., Papageorgiou, C., and Subramanian, A. (2009). "Is Newer Better? Penn World Table Revisions and Their Impact on Growth Estimates." National Bureau of Economic Research Working Paper 1545.
- Karpoff, Jonathan M. and Lee, D. Scott and Martin, Gerald S. (2017). "Foreign Bribery: Incentives and Enforcement." Working Paper.
- Mamo, N., Bhattacharyya, S., and Moradi, A. (2019). "Intensive and Extensive Margins of Mining and Development: Evidence from Sub-Saharan Africa." *Journal of Development Economics* 139: 28–49
- Martin, G., Karpoff, J., Lee, D., and Cooper, J. (2012). "The Foreign Corrupt Practices Act: An Empirical Examination of Enforcement Trends." Working paper.
- Mehlum, H., Moene, K. and Torvik, R. (2006). "Institutions and the Resource Curse." *Economic Journal*, 116: 1–20.
- Melgar, N., Rossi, M., and Smith, T.W. (2010). "The Perception of Corruption." *International Journal of Public Opinion Research*, 22 (1): 120–131.
- Michalopoulos, S., and Papaioannou, E. (2013). "Pre-Colonial Ethnic Institutions and Contemporary African Development." *Econometrica*, 81: 113–152.
- Michalopoulos, S., and Papaioannou, E. (2014). "National Institutions and Subnational Development in Africa." *Quarterly Journal of Economics*, 129(1), 151–213.
- Mocan, N. (2004). "What Determines Corruption? International Evidence from Micro Data." NBER Working Paper, No. 10460.
- OECD. (2014). *Foreign Bribery Report: An Analysis of the Crime of Bribery of Foreign Public Officials*. Paris: OECD Publishing.
- OECD (2016). *Corruption in the Extractive Value Chain – Typology of Risks, Mitigation Measures and Incentives*. OECD
- OECD (2019). *2018 Enforcement of the Anti-Bribery Convention - Investigations, proceedings, and sanctions*. OECD Working Group on Bribery, December 2019

- Olken B.A. (2007). "Monitoring Corruption: Evidence from a Field Experiment in Indonesia." *Journal of Political Economy* 115(2), 200–249.
- Olken, B. A., & Pande, R. (2012). "Corruption in Developing Countries." *Annual Review of Economics*, 4(1), 479–509.
- Ortiz-Ospina, E., and Roser, M. (2016). "Corruption." *Our World in Data*. Retrieved from: <https://ourworldindata.org/corruption>.
- Ramey, G., & Ramey, V. (1995). "Cross-Country Evidence on the Link between Volatility and Growth." *American Economic Review*, 85(5), 1138–1151.
- Rauter, T. (2020). "The Impact of Mandatory Extraction Payment Disclosures on Corporate Payment and Investment Policies Abroad." *Journal of Accounting Research*. Forthcoming.
- Robinson, J. A., Torvik, R., and Verdier, T. (2006). "Political Foundations of the Resource Curse." *Journal of Development Economics*, 79(2), 447–468.
- Sachs, J., and Warner, A. (1995). "Natural Resource Abundance and Economic Growth." NBER Working Paper, No 5398.
- Sanseverino, A. (2020). "The Impact of Anti-Corruption Laws: Evidence from the U.K. Bribery Act's Extraterritorial Reach." Working Paper.
- Sarr, M., Bulte, E., Meissner, C., and Swanson, T. (2011). "On the Looting of Nations." *Public Choice*, 148: 353–380.
- Smith, B. (2015). "The Resource Curse Exorcised: Evidence from a Panel of Countries." *Journal of Development Economics*, 116, 57–73.
- Shleifer, A., & Vishny, R.W. (1993). "Corruption." *Quarterly Journal of Economics* 108(3), 599–617.
- Torgler, B., and Valev, N.T. (2006). "Corruption and Age." *Journal of Bioeconomics* 8:133–145
- UNCTAD. (2012). "Extractive industries: Optimizing Value Retention in Host Countries." UNCTAD/SUC. New York and Geneva, United Nations
- U.S. Department of Justice & U.S. Securities and Exchange Commission. (2012). *A Resource Guide to the U.S. Foreign Corrupt Practices Act*. Washington D.C.: U.S. Department of Justice. Retrieved from: <https://www.justice.gov/criminal-fraud/fcpa-guidance>.
- U.S. Securities and Exchange Commission. (2017). *In the Matter of Halliburton Company*. Release No. 81222. Retrieved from: <https://www.sec.gov/litigation/admin/2017/34-81222.pdf>
- Zamboni, Y., & Litschig, S. (2018). "Audit Risk and Rent Extraction: Evidence from a Randomized Evaluation in Brazil." *Journal of Development Economics*, (134), 133–149.
- Zeume, S. (2017). "Bribes and Firm Value." *Review of Financial Studies*, 30(5), 1457–1489.

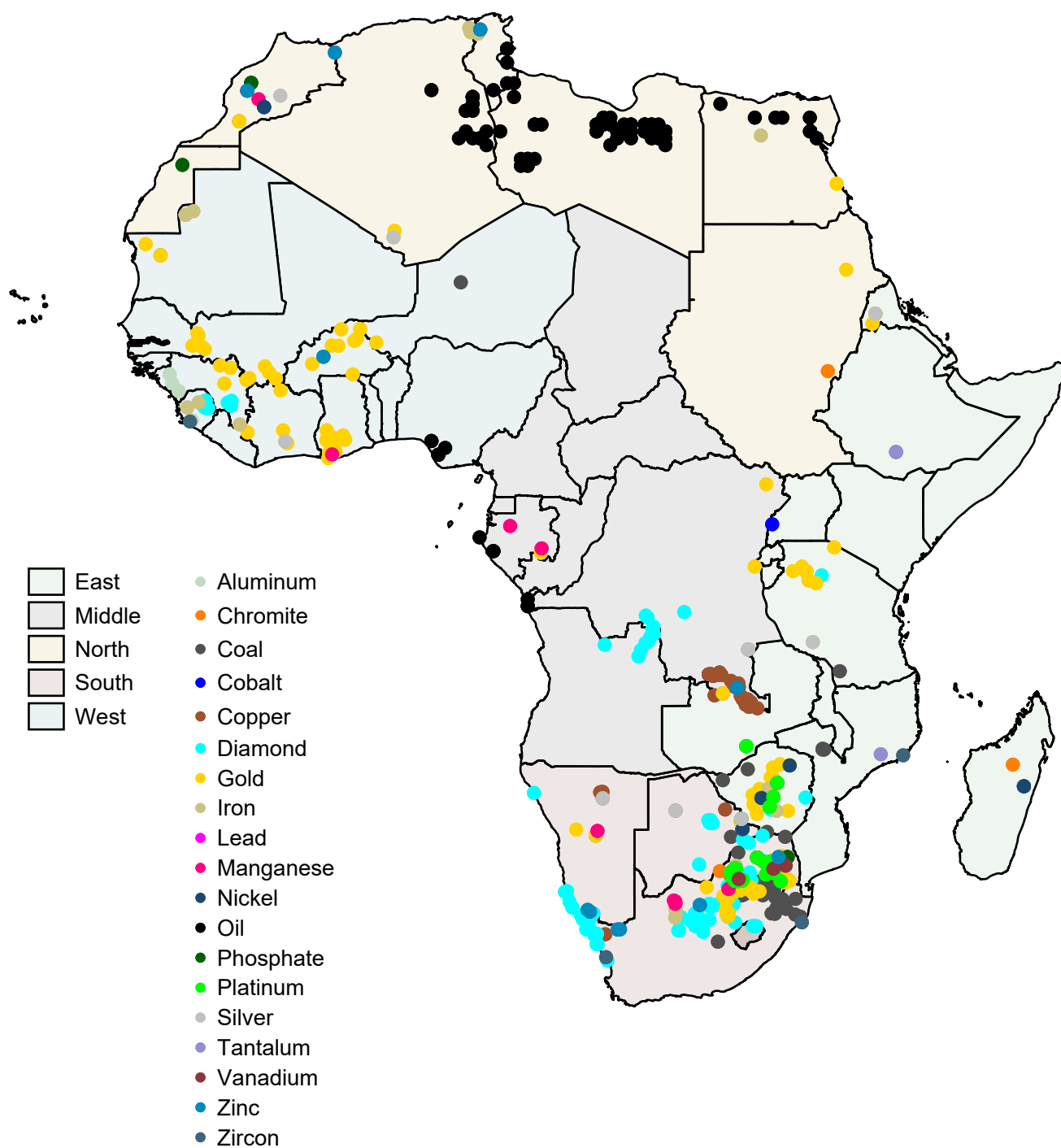
Figure 1: Geographical Distribution of Treated and Control Extraction Facilities



*Notes:* This figure shows the geographical location of treated and control facilities in our sample. Treated extraction facilities have at least one significant owner (with more than 20% ownership stake) in 2004 who is headquartered, cross-listed, or operates a segment in the US and is from an ABC-signatory country (see Internet Appendix Table IA1). All other extraction facilities belong to the control group. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International.

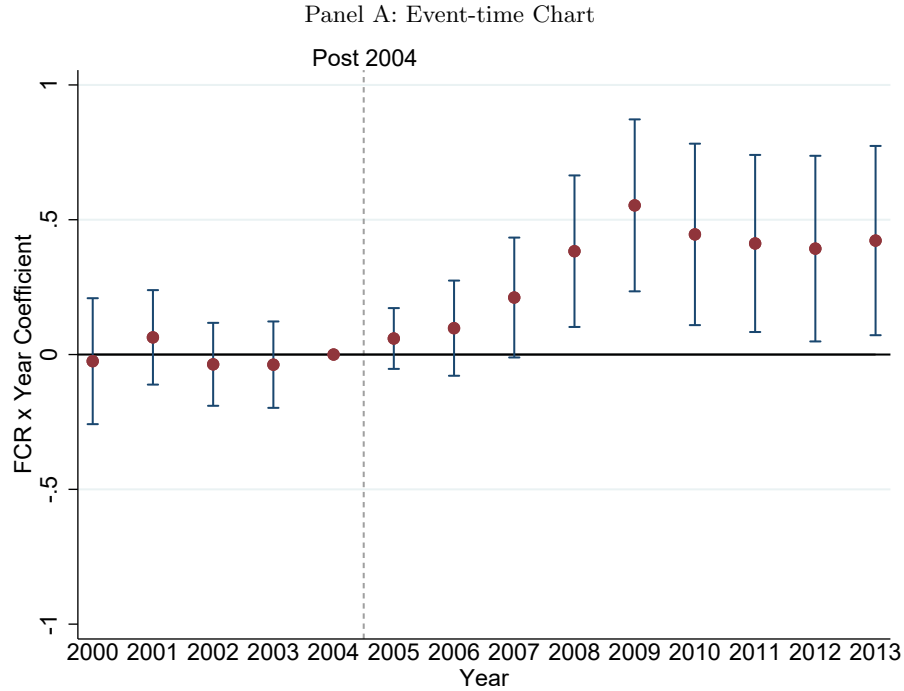


Figure 2: Geographical Distribution of Extraction Facilities by Commodity

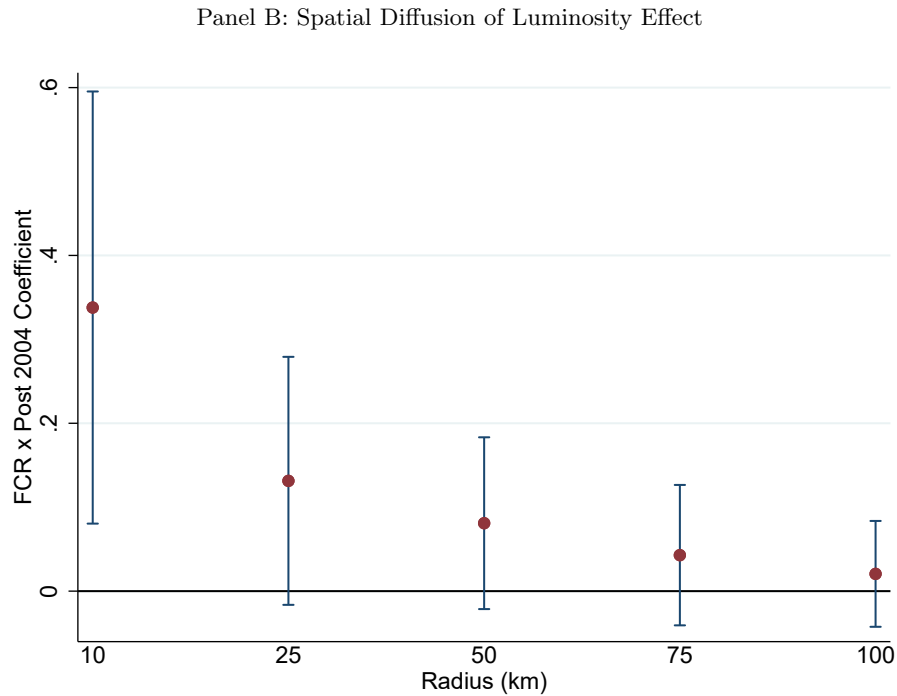


*Notes:* This figure shows the geographical location of extraction facilities in our sample by commodity. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International.

**Figure 3: Foreign Corruption Regulation and Economic Activity in Extraction Areas**

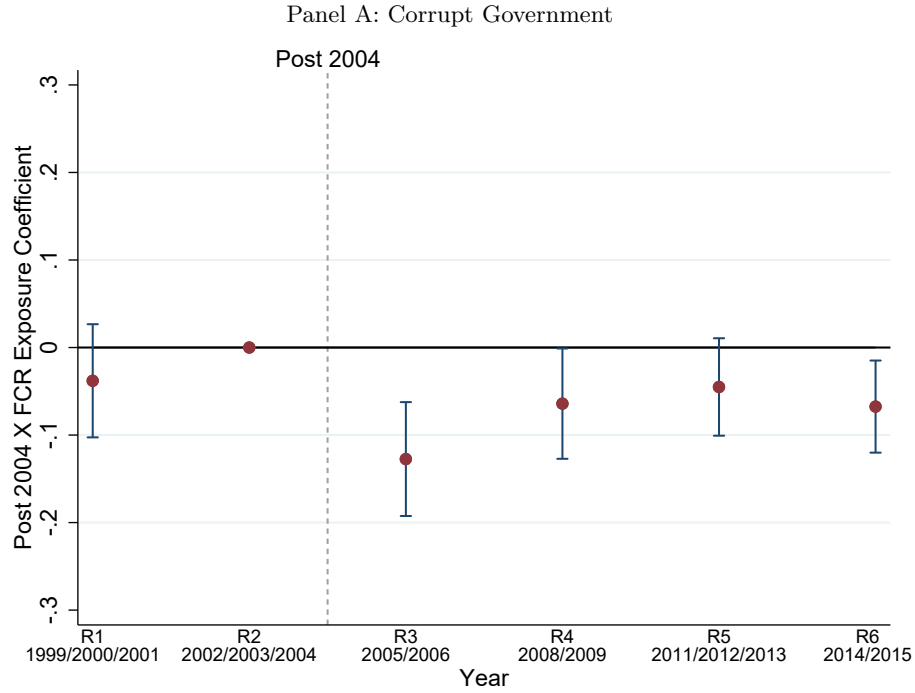


*Notes:* Panel A shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on nighttime luminosity. We estimate the model from Column (1) of Table 4 but replace the  $FCR \times Post\ 2004$  indicator with separate interactions for each of the years in our sample (except for 2004, which serves as the benchmark).

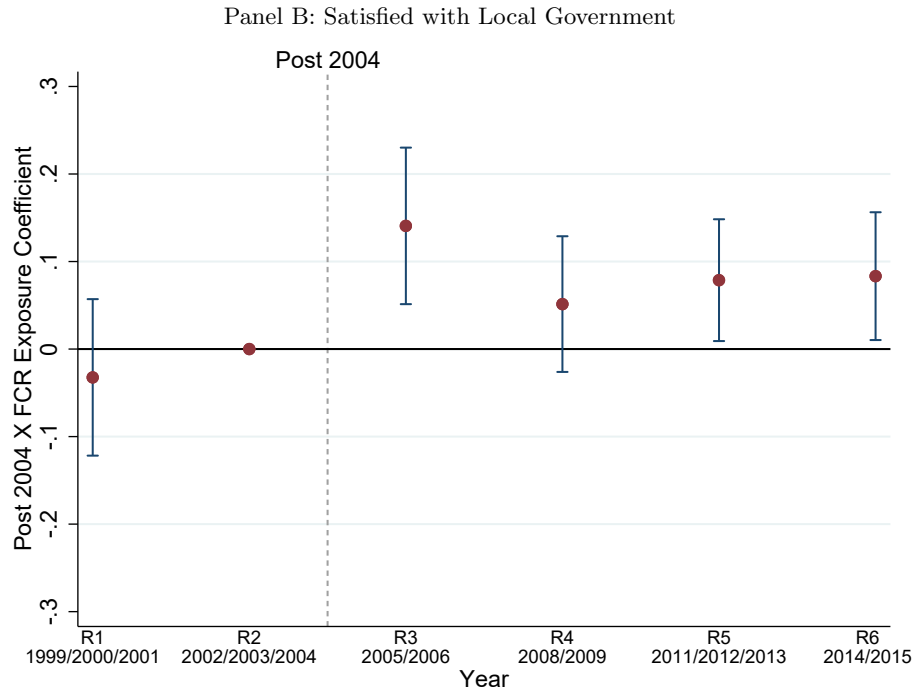


*Notes:* Panel B shows coefficient estimates of  $FCR \times Post\ 2004$  and 95% confidence intervals for cell areas with radii of 10km, 25km, 50km, 75km, and 100km, respectively. We estimate the model from Column (1) of Table 4 but use different cell areas for our dependent variable  $\ln(Luminosity + 0.01)$ .

**Figure 4: Foreign Corruption Regulation, Perceptions of Corruption, and Satisfaction with Local Officials**



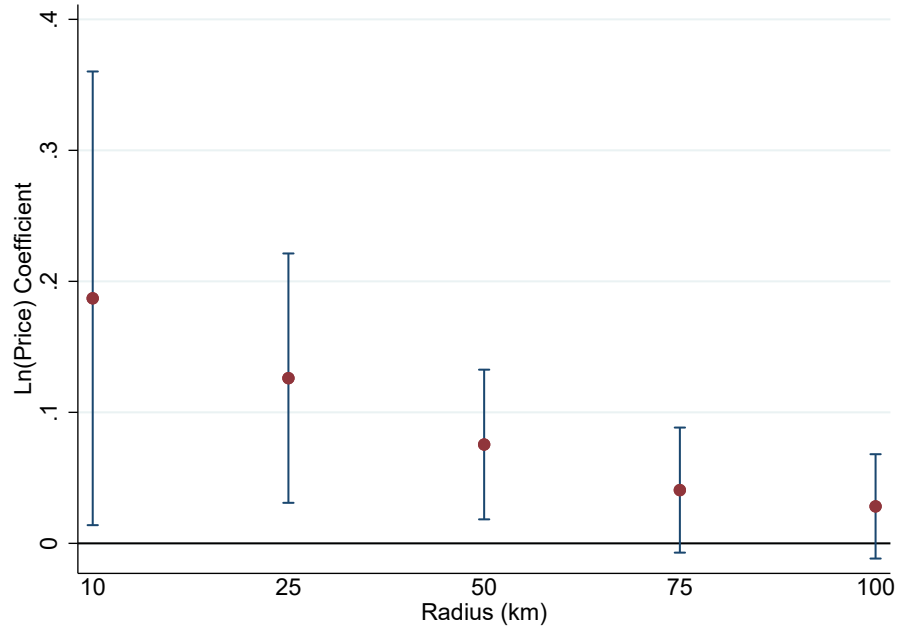
*Notes:* Panel A shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on the perceived corruption of government officials. We estimate the model from Column (1) of Table 5 Panel B, but replace the  $FCR\ Exposure \times Post\ 2004$  indicator with separate interactions for each survey round in our sample (except for Round 2, which serves as the benchmark).



*Notes:* Panel B shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on the perceived satisfaction with local governments. We estimate the model from Column (3) of Table 5 Panel B, but replace the  $FCR\ Exposure \times Post\ 2004$  indicator with separate interactions for each survey round in our sample (except for Round 2, which serves as the benchmark).

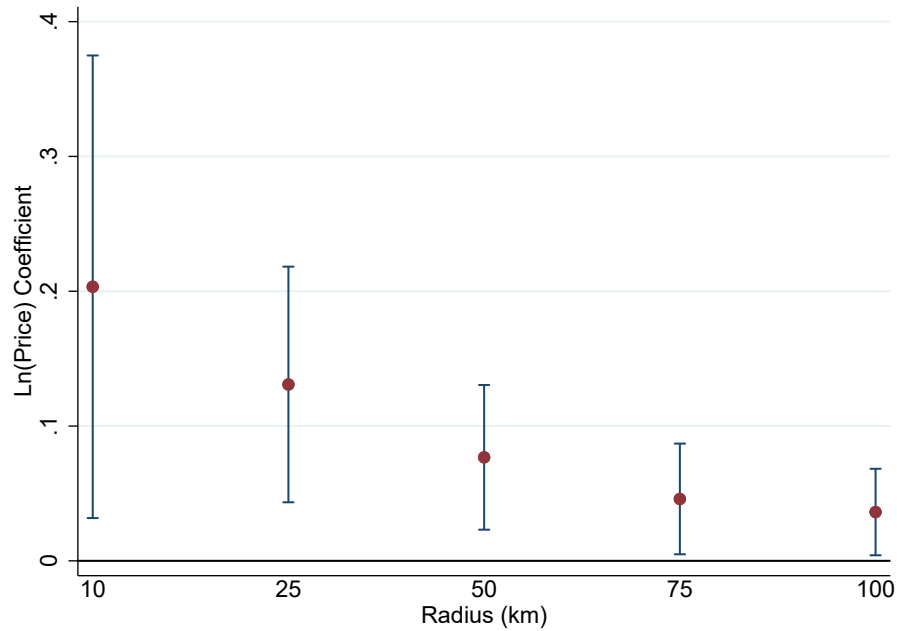
**Figure 5: Unconditional Association between Commodity Prices and Luminosity**

Panel A: With Property and Year Fixed Effects



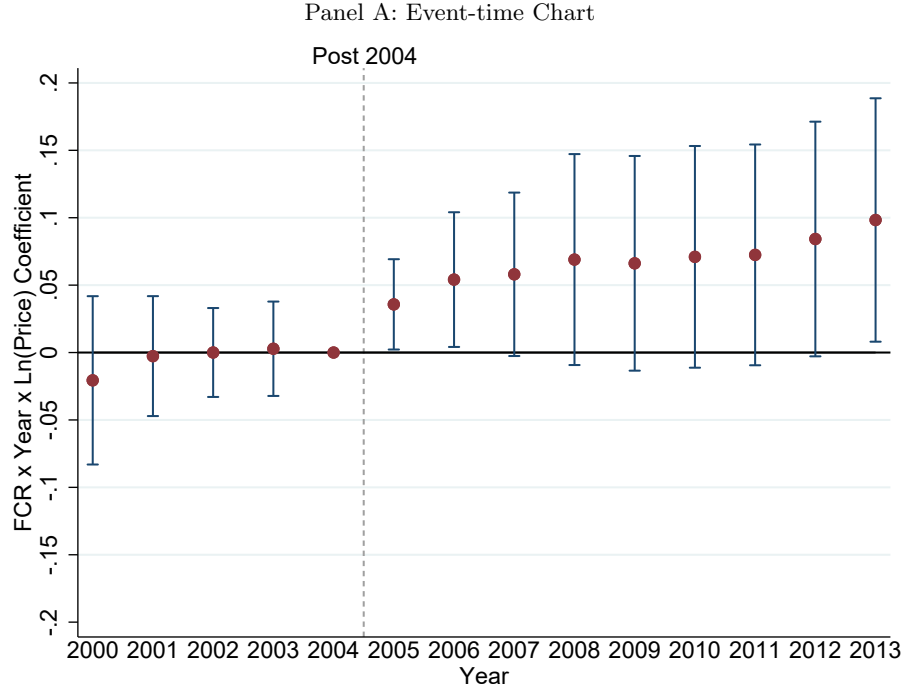
*Notes:* Panel A shows the coefficient estimates and 95% confidence intervals of OLS regressions estimating the association between world commodity prices and nighttime luminosity for cell areas with radii of 10km, 25km, 50km, 75km, and 100km, respectively.

Panel B: With Property and Region  $\times$  Year Fixed Effects

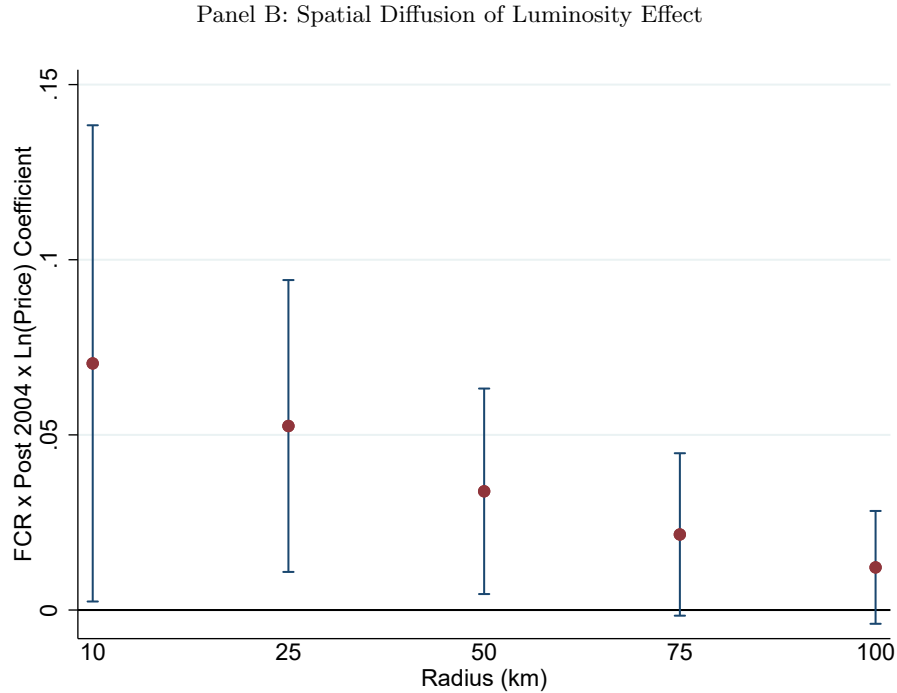


*Notes:* Panel B shows the coefficient estimates and 95% confidence intervals of OLS regressions estimating the association between world commodity prices and nighttime luminosity for cell areas with radii of 10km, 25km, 50km, 75km, and 100km, respectively.

**Figure 6: Foreign Corruption Regulation and the Contribution of Resource Extraction to Development**



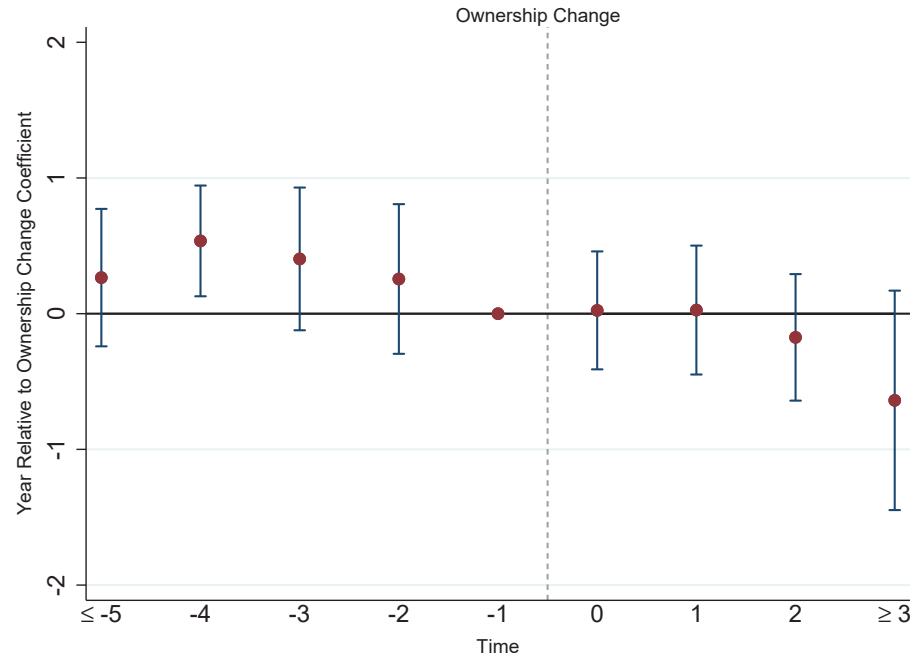
*Notes:* Panel A shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on the association between world commodity prices and nighttime luminosity. We estimate the model from Column (1) of Table 6 Panel B but replace the  $FCR \times Post\ 2004 \times Ln(Price)$  indicator with separate interactions for each of the years in our sample (except for 2004, which serves as the benchmark).



*Notes:* Panel B shows coefficient estimates of  $FCR \times Post\ 2004 \times Ln(Price)$  and 95% confidence intervals for cell areas with radii of 10km, 25km, 50km, 75km, and 100km, respectively. We estimate the model from Column (1) of Table 6 Panel B but use different cell areas for our dependent variable  $Ln(Luminosity + 0.01)$ .

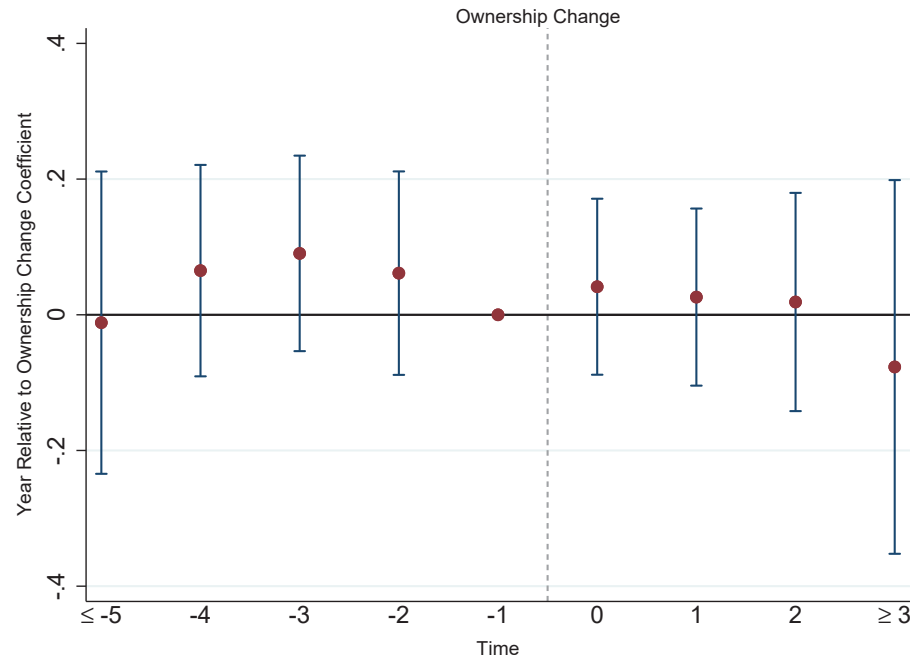
**Figure 7: Foreign Corruption Regulation and Within Extraction Sector Resource Allocation**

Panel A: Economic Activity in Extraction Areas



*Notes:* Panel A shows coefficient estimates and 95% confidence intervals for OLS regressions examining changes in nighttime luminosity around ownership changes of FCR mines after 2004.

Panel B: Contribution of Resource Extraction to Development



*Notes:* Panel B shows coefficient estimates and 95% confidence intervals for OLS regressions examining changes in the association between commodity prices and nighttime luminosity around ownership changes of FCR mines after 2004.

**Table 1: Sample Composition**

	Unique Properties	Unique Foreign Properties	Unique USJ Properties	Unique FCR Properties	Property-Year Observations	FCR Property-Year Observations
Aluminum	5	3	2	2	70	28
Chromite	18	10	10	8	252	112
Coal	102	35	46	31	1,428	434
Cobalt	22	15	9	5	308	70
Copper	73	37	28	13	1,022	182
Diamond	85	43	9	1	1,190	14
Gold	170	76	87	28	2,380	392
Iron	19	2	6	2	266	28
Lead	7	5	5	3	98	42
Manganese	11	5	3	2	154	28
Nickel	36	11	13	2	504	28
Oil	99	19	7	4	1,386	56
Phosphate	4	0	0	0	56	0
Platinum	39	12	15	1	546	14
Silver	12	7	3	1	168	14
Tantalum	3	0	0	0	42	0
Vanadium	3	2	2	2	42	28
Zinc	11	8	9	6	154	84
Zircon	4	3	2	2	56	28
Total	723	293	256	113	10,122	1,582

*Notes:* This table presents descriptive statistics by commodity for our luminosity sample. We define all variables in Appendix A. We describe the sample selection in Table IA2 of the Internet Appendix. The sample is from 2000 to 2013. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. SEC filing data is from the S&P and SeekEdgar databases. We collect geographic segment-level data and financial data from Worldscope.

**Table 2: Characteristics of Extraction Areas**

**Panel A: Employment in Mining Sector**

	Number of Respondents	Fraction of Mine Workers	Difference Mining vs. Non-Mining Areas
Mining Areas:			
0-10km	1,407	0.182	0.177***
0-25km	5,115	0.154	0.149***
0-50km	15,874	0.097	0.092***
0-75km	32,206	0.074	0.069***
0-100km	54,817	0.070	0.065***
Non-Mining Areas	15,260	0.005	

*Notes:* This table presents descriptive statistics for mining-related employment in mining and non-mining areas. Mine-level data is from the SNL Metals and Mining Database. We collect survey data from round 2 of the Afrobarometer.

**Panel B: Perceived Corruption of Foreign Businessmen**

	Number of Respondents	Perceived Corruption of Foreign Businessmen	Difference Extraction vs. Non-Extraction Areas
Extraction Areas (0-100km)	52,046	0.057	0.078***
Non-Extraction Areas	12,454	-0.021	

*Notes:* This table presents descriptive statistics for corruption perceptions of foreign businessmen in extraction and non-extraction areas. We de-mean *Perceived Corruption of Foreign Businessmen* before computing averages for extraction areas and non-extraction areas. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. We collect survey data from round 2 of the Afrobarometer.



**Table 3: Descriptive Statistics**

	N	Mean	SD	P1	P25	P50	P75	P99
<i>Luminosity (10)</i>	10,122	7.738	10.423	0.000	0.510	3.108	10.486	44.358
<i>Luminosity (1-10)</i>	10,122	7.672	10.393	0.000	0.492	3.031	10.339	44.233
<i>Luminosity (25)</i>	10,122	4.841	6.431	0.000	0.408	2.076	7.208	28.713
<i>Luminosity (50)</i>	10,122	3.590	4.648	0.000	0.318	1.677	4.940	20.474
<i>Luminosity (75)</i>	10,122	3.177	4.126	0.002	0.276	1.605	4.029	17.708
<i>Luminosity (100)</i>	10,122	2.942	3.640	0.006	0.270	1.354	3.889	13.604
<i>FCR</i>	10,122	0.156	0.363	0.000	0.000	0.000	0.000	1.000
<i>USJ Non-OECD</i>	10,122	0.203	0.402	0.000	0.000	0.000	0.000	1.000
<i>Post 2004</i>	10,122	0.643	0.479	0.000	0.000	1.000	1.000	1.000
<i>Price</i>	8,694	6,430.251	10334.401	0.024	1.450	51.800	10400.000	38200.000

*Notes:* This table presents descriptive statistics for the luminosity analyses in Table 4 and Table 6 Panel B. We define all variables in Appendix A. We describe the sample selection in Table IA2 of the Internet Appendix. The sample is from 2000 to 2013. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. SEC filing data is from the S&P and SeekEdgar databases. World commodity price data is from the United States Geological Survey and the World Bank. Luminosity data is from the National Centers for Environmental Information (NOAA). We collect geographic segment-level data and financial data from Worldscope.

**Table 4: Foreign Corruption Regulation and Economic Activity in Extraction Areas**

	Baseline	Sensitivity Analyses		
	(1)	(2)	(3)	(4)
Dependent Variable: $\text{Ln}(\text{Luminosity (10)} + 0.01)$	0-10 km Radius	1-10 km Radius	Within Region $\times$ Year	Placebo Test: USJ Non-OECD
<i>FCR <math>\times</math> Post 2004</i>	0.338** (2.57)	0.320** (2.46)	0.301** (2.49)	
<i>USJ Non-OECD <math>\times</math> Post 2004</i>				0.015 (0.14)
Fixed Effects:				
Property $\times$ Commodity	Yes	Yes	Yes	Yes
Region $\times$ Year	No	No	Yes	No
Commodity $\times$ Year	Yes	Yes	Yes	Yes
Property-Commodity-Year Observations	10,122	10,122	10,122	6,958

*Notes:* This table reports coefficient estimates of OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on nighttime luminosity in extraction areas. We define all variables in Appendix A. We describe the sample selection in Table IA2 of the Internet Appendix. The sample is from 2000 to 2013. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. SEC filing data is from the S&P and SeekEdgar databases. World commodity price data is from the United States Geological Survey and the World Bank. Luminosity data is from the National Centers for Environmental Information (NOAA). We collect geographic segment-level data and financial data from Worldscope. T-statistics, reported in parentheses, are based on Conley (1999) standard errors allowing for spatial correlation within a 500km radius and for infinite serial correlation. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

**Table 5: Effect of Foreign Corruption Regulation on Perceptions of Corruption and Satisfaction with Local Officials**

**Panel A: Descriptive Statistics**

	N	Mean	SD	P1	P25	P50	P75	P99
<i>FCR Exposure</i>	57,629	0.174	0.379	0.000	0.000	0.000	0.000	1.000
<i>Corrupt Government</i>	57,629	0.442	0.497	0.000	0.000	0.000	1.000	1.000
<i>Satisfied with Local Government</i>	50,741	0.518	0.500	0.000	0.000	1.000	1.000	1.000
<i>Post 2004</i>	57,629	0.766	0.423	0.000	1.000	1.000	1.000	1.000
<i>Female</i>	57,577	0.490	0.500	0.000	0.000	0.000	1.000	1.000
<i>Urban</i>	56,704	0.437	0.496	0.000	0.000	0.000	1.000	1.000
<i>Age</i>	57,201	37.156	14.804	18.000	25.000	34.000	46.000	79.000

*Notes:* This table presents descriptive statistics for the perception analyses in Table 5 Panel B. We define all variables in Appendix A. The sample is from 1999 to 2015. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. SEC filing data is from the S&P and SeekEdgar databases. We collect geographic segment-level data and financial data from Worldscope. We collect survey data from rounds 1 to 6 of the Afrobarometer.

**Panel B: Regressions**

	Corrupt Government		Satisfied with Local Government	
	(1)	(2)	(3)	(4)
	Baseline	Including Controls	Baseline	Including Controls
<i>FCR Exposure</i> $\times$ <i>Post 2004</i>	-0.044** (-2.32)	-0.044** (-2.27)	0.103*** (4.11)	0.103*** (4.03)
<i>FCR Exposure</i>	-0.000 (-0.02)	0.005 (0.29)	-0.052** (-2.17)	-0.060** (-2.51)
Controls:				
<i>Female</i>		-0.021*** (-5.73)		0.010*** (2.59)
<i>Urban</i>		0.055*** (9.14)		-0.069*** (-9.54)
<i>Ln(Age)</i>		-0.018*** (-3.26)		0.051*** (8.22)
Fixed Effects:				
Region $\times$ Year	Yes	Yes	Yes	Yes
Mineral	Yes	Yes	Yes	Yes
Standard Error Clusters:				
Village	4,535	4,530	4,343	4,339
Adjusted R-Squared	0.052	0.055	0.050	0.057
Observations	57,629	56,229	55,817	54,380

*Notes:* This table reports coefficient estimates of OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on the perceived corruption of government officials and the perceived satisfaction with local governments. We define all variables in Appendix A. The sample is from 1999 to 2015. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. SEC filing data is from the S&P and SeekEdgar databases. We collect geographic segment-level data and financial data from Worldscope. We collect survey data from rounds 1 to 6 of the Afrobarometer. T-statistics, reported in parentheses, are based on standard errors clustered at the village level. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

**Table 6: Extraction Activities' Contribution to Economic Growth****Panel A: Association between World Mineral Prices and Local Mineral Production**

	(1)	(2)
Dependent Variable:	Ln(Production+0.01)	Ln(Production+0.01)
<i>Ln(Price)</i>	1.045** (2.27)	0.989** (2.20)
Fixed Effects:		
Property $\times$ Commodity	Yes	Yes
Year	Yes	No
Region $\times$ Year	No	Yes
Property-Commodity-Year Observations	7,350	7,350

*Notes:* This table reports the coefficient estimates of OLS regressions estimating the association between world commodity prices and property-level production. We define all variables in Appendix A. We describe the sample selection in Table IA2 of the Internet Appendix. The sample is from 2000 to 2013. World commodity price data is from the United States Geological Survey and the World Bank. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. T-statistics, reported in parentheses, are based on Conley (1999) standard errors allowing for spatial correlation within a 500km radius and for infinite serial correlation. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

**Panel B: Foreign Corruption Regulation and the Contribution of Resource Extraction to Development**

	Baseline	Sensitivity Analyses		
	(1)	(2)	(3)	(4)
Dependent Variable: Ln(Luminosity (10) + 0.01)	0-10 km Radius	1-10 km Radius	Within Region $\times$ Year	Placebo Test: USJ Non-OECD
<i>FCR <math>\times</math> Post 2004 <math>\times</math> Ln(Price)</i>	0.070** (2.03)	0.073** (2.14)	0.054 (1.62)	
<i>FCR <math>\times</math> Ln(Price)</i>	0.158 (0.49)	0.177 (0.56)	0.148 (0.48)	
<i>USJ Non-OECD <math>\times</math> Post 2004 <math>\times</math> Ln(Price)</i>				-0.017 (-0.63)
<i>USJ Non-OECD <math>\times</math> Ln(Price)</i>				-0.302* (-1.71)
Fixed Effects:				
Property $\times$ Commodity	Yes	Yes	Yes	Yes
Region $\times$ Year	No	No	Yes	No
Commodity $\times$ Year	Yes	Yes	Yes	Yes
FCR $\times$ Year	Yes	Yes	Yes	Yes
Property-Commodity-Year Observations	8,694	8,694	8,694	5,964

*Notes:* This table reports coefficient estimates of OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on the association between world commodity prices and nighttime luminosity. We define all variables in Appendix A. We describe the sample selection in Table IA2 of the Internet Appendix. The sample is from 2000 to 2013. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. SEC filing data is from the S&P and SeekEdgar databases. World commodity price data is from the United States Geological Survey and the World Bank. Luminosity data is from the National Centers for Environmental Information (NOAA). We collect geographic segment-level data and financial data from Worldscope. T-statistics, reported in parentheses, are based on Conley (1999) standard errors allowing for spatial correlation within a 500km radius and for infinite serial correlation. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

## Appendix A: Variable Definitions

### Variables used in Extraction Area Analysis

<i>Mining Area</i>	Binary indicator equal to one if the distance between the mine and survey location is less than or equal to 100km.
<i>Fraction of Mining Workers</i>	The fraction of workers that indicated their main occupation as <i>Miner</i> based on the Afrobarometer survey question: <i>What is your main occupation? (If unemployed, retired, or disabled, what was your last main occupation?)</i>
<i>Extraction Area</i>	Binary indicator equal to one if the distance between the extraction property and survey location is less than or equal to 100km.
<i>Perceived Corruption of Foreign Businessmen</i>	The average response value for the Afrobarometer survey question: <i>How many of the following people do you think are involved in corruption, or haven't you heard enough about them to say: Foreign businessmen?</i> 0=None, 1=Some of them, 2= Most of them, 3=All of them.

### Variables used in Luminosity Analysis

<i>Luminosity (10)</i>	Stable light mean unsaturated nighttime luminosity within a 10 km radius of the respective property.
<i>Luminosity (1-10)</i>	Stable light mean unsaturated nighttime luminosity within a 1-10 km radius of the respective property.
<i>Luminosity (25)</i>	Stable light mean unsaturated nighttime luminosity within a 25 km radius of the respective property.
<i>Luminosity (50)</i>	Stable light mean unsaturated nighttime luminosity within a 50 km radius of the respective property.
<i>Luminosity (75)</i>	Stable light mean unsaturated nighttime luminosity within a 75 km radius of the respective property.
<i>Luminosity (100)</i>	Stable light mean unsaturated nighttime luminosity within a 100 km radius of the respective property.
<i>FCR</i>	Binary indicator equal to one if an extraction facility has at least one significant owner (with more than 20% ownership stake) in 2004 who is headquartered, cross-listed, or operates a segment in the US and is from an OECD ABC-signatory country.
<i>USJ Non-OECD</i>	Binary indicator equal to one if a property has at least one significant owner (with more than 20% ownership stake) in 2004 who is cross-listed or operates a segment in the US but is not from an OECD ABC-signatory country.
<i>Post 2004</i>	Binary indicator equal to one for years after 2004.
<i>Price</i>	World price of a given commodity in a given year.
<i>Production</i>	Reported actual production of the respective commodity (in metric tonnes) in a given year multiplied by the world commodity price in 2000.

### Variables used in Perception Analysis

<i>FCR Exposure</i>	Binary indicator equal to one if the closest extraction facility within 100 km of a survey respondent has at least one significant owner (with more than 20% ownership stake) in 2004 who is headquartered, cross-listed, or operates a segment in the US and is from an OECD ABC-signatory country.
<i>Corrupt Government</i>	Binary indicator equal to one if the response value to the following Afrobarometer survey question equals 2=Most of them or 3=All of them: <i>How many of the following people do you think are involved in corruption, or haven't you heard enough about them to say: Government officials?</i>
<i>Satisfied with Local Government</i>	Binary indicator equal to one if the response value to the following Afrobarometer survey question equals 3=Approve or 4=Strongly approve: <i>Do you approve or disapprove of the way the following people have performed their jobs over the past twelve months, or haven't you heard enough about them to say: Your Local Government/official/assembly?</i>
<i>Post 2004</i>	Binary indicator equal to one for years after 2004.
<i>Female</i>	Binary indicator equal to one if the respondent's gender is female.
<i>Urban</i>	Binary indicator equal to one if the respondent lives in an urban area.
<i>Age</i>	The age of the respondent.

Internet Appendix to

**Reversing the Resource Curse:  
Foreign Corruption Regulation and Economic Development**

**Table of Contents**

**Section IA1: FCPA Enforcement Increase**

Figure IA1: FCPA Enforcement Actions against Non-US Firms by Parent Company Origin

Table IA1: Institutional Details on OECD Anti-Bribery Convention

**Section IA2: Sample Selection**

Table IA2: Sample Selection Criteria

**Section IA3: Supplementary Tests for Luminosity Analyses**

Figure IA2: Luminosity Effects in Event-Time Excluding Overlapping Extraction Areas

Figure IA3: Luminosity Effects in Event-Time Keeping Only Main Minerals

Figure IA4: Luminosity Effects in Event-Time Including Mines with Zero Reported Production

Figure IA5: Treatment Effects in Event-Time using Ln(Luminosity) as Outcome Variable

Figure IA6: Spatial Diffusion of Treatment Effects using Ln(Luminosity) as Outcome Variable

Figure IA7: Luminosity Effects in Event-Time Excluding Gold

Figure IA8: Placebo Difference-in-Differences Results in Event-Time

Table IA3: Luminosity Effects Excluding Overlapping Extraction Areas

Table IA4: Luminosity Effects Keeping Only Main Minerals

Table IA5: Luminosity Effects Including Mines with Zero Reported Production

Table IA6: Jackknife Procedure Excluding Individual Minerals

**Section IA4: Supplementary Tests for Perceptions Analyses**

Table IA7: Survey Respondents in Extraction Areas by Country and Round

Table IA8: Perception Results Excluding Afrobarometer Survey Round 1

**Section IA5: Supplementary Tests for Mechanism Analyses**

Figure IA9: Mining Occupation Effects in Event-Time

Figure IA10: Mineral Production Effects in Event-Time

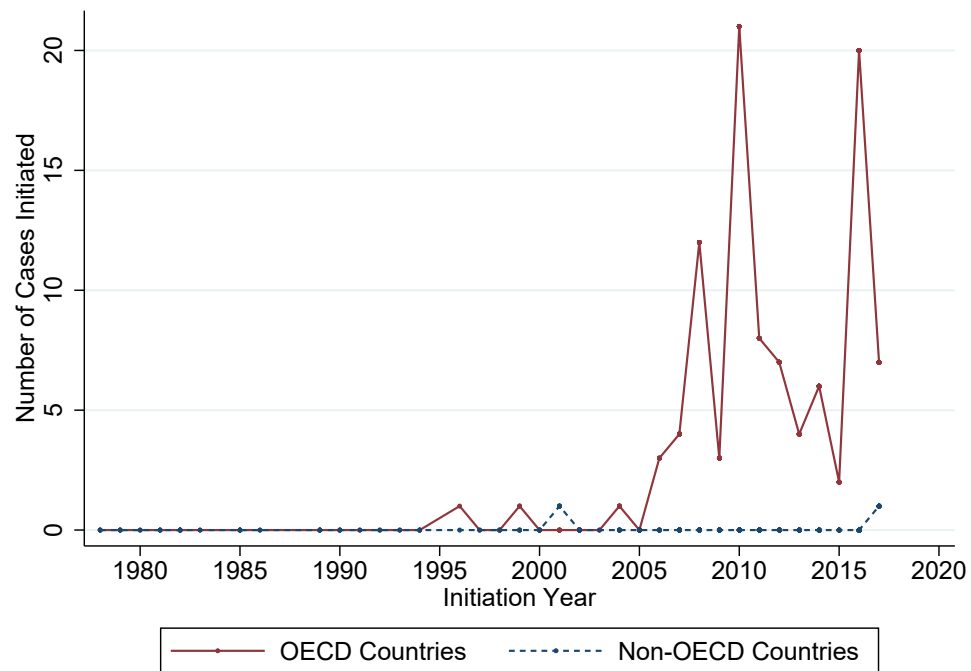
Figure IA11: Commodity Prices over Time

Figure IA12: Luminosity Effects in Event-Time with Region  $\times$  Year Fixed Effects

Table IA9: Effect of Foreign Corruption Regulation on Mining Occupation

Table IA10: Effect of Foreign Corruption Regulation on Mineral Production

**Figure IA1: FCPA Enforcement Actions against Non-US Firms by Parent Company Origin**



*Notes:* This figure shows the annual number of FCPA enforcement actions initiated by the SEC and DOJ against firms from non-US OECD and non-US, non-OECD countries from 1977 to 2017. We collect all (337) enforcement actions against corporations from the Stanford Law School FCPA Database.

**Table IA1: Institutional Details on  
OECD Anti-Bribery Convention**

Country	FCPA Enforcement Actions
Argentina	0
Australia	0
Austria	0
Belgium	1
Brazil	5
Bulgaria	0
Canada	2
Chile	4
Czech Republic	0
Denmark	3
Finland	0
France	8
Germany	15
Greece	0
Hungary	1
Iceland	0
Ireland	0
Israel	2
Italy	5
Japan	5
Luxembourg	3
Mexico	1
Netherlands	8
New Zealand	0
Norway	2
Poland	1
Portugal	0
Slovak Republic	0
Slovenia	0
South Korea	0
Spain	0
Sweden	5
Switzerland	11
Turkey	0
United Kingdom	13
United States	236

*Notes:* This table presents implementation characteristics of the OECD Anti-Bribery Convention (ABC) for signatory countries that ratified the convention before 2004.

**Table IA2: Sample Selection Criteria****Panel A: Mining Sample**

Sample Selection Step	Mine Observations	Luminosity Observations	$\Delta$
Raw mine level data (downloaded from the SNL Database in Dec. 2018)			
(1) Raw mine observations	3,842		
(2) Excluding mines with zero reported production from 2000 to 2013	487		-3,355
(3) Adding observations for mines that produce multiple minerals	673		+186
Luminosity data			
(4) Luminosity observations at the mine-mineral-year level		9,422	$\times 14$
(5) Excluding minerals with no price data		8,778	-644
(6) Excluding singletons		8,736	-42
Final baseline sample of mine-mineral-year observations		8,736	

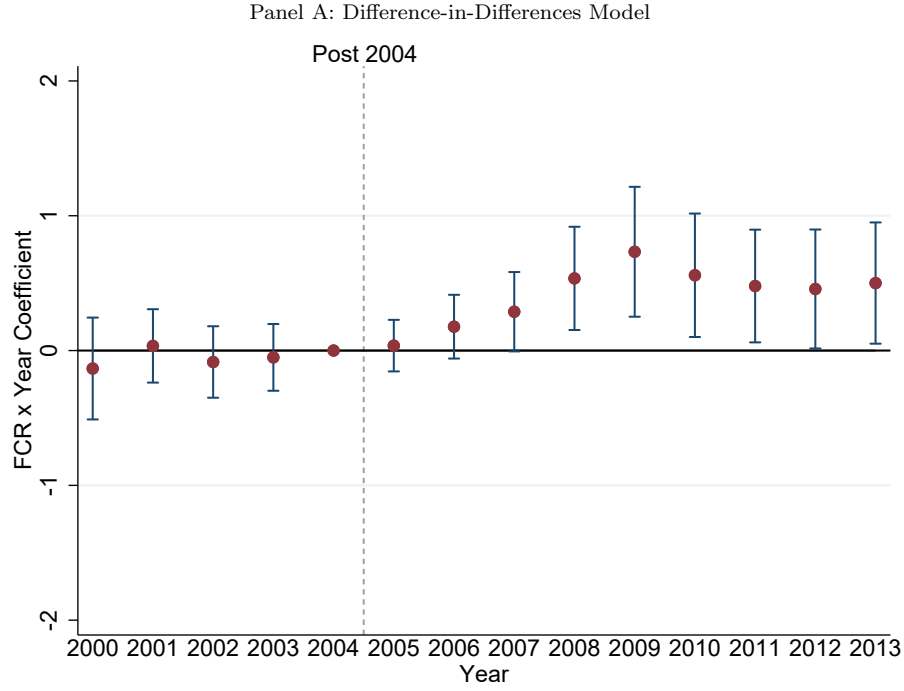
**Panel B: Oil Well Sample**

Sample Selection Step	Oil Well Observations	Luminosity Observations	$\Delta$
Raw oil well data (downloaded from Enverus International in June 2019)			
(1) Raw oil well observations	3,026		
(2) Excluding duplicate observations	3,021		-5
(3) Excluding observations with no location data	3,012		-9
(4) Excluding wells discovered after 2004	2,404		-608
(5) Excluding wells located in blocks where multiple firms operate	272		-2,132
(6) Excluding wells that only produce gas	231		-41
(7) Excluding offshore wells	166		-65
(8) Excluding non-land environments	164		-2
(9) Excluding abandoned, shut in, depleted, or discovery wells	100		-64
(10) Excluding wells with no luminosity data	99		-1
Luminosity data			
(11) Luminosity observations at the well-year level		1,386	$\times 14$
Final baseline sample of well-year observations		1,386	

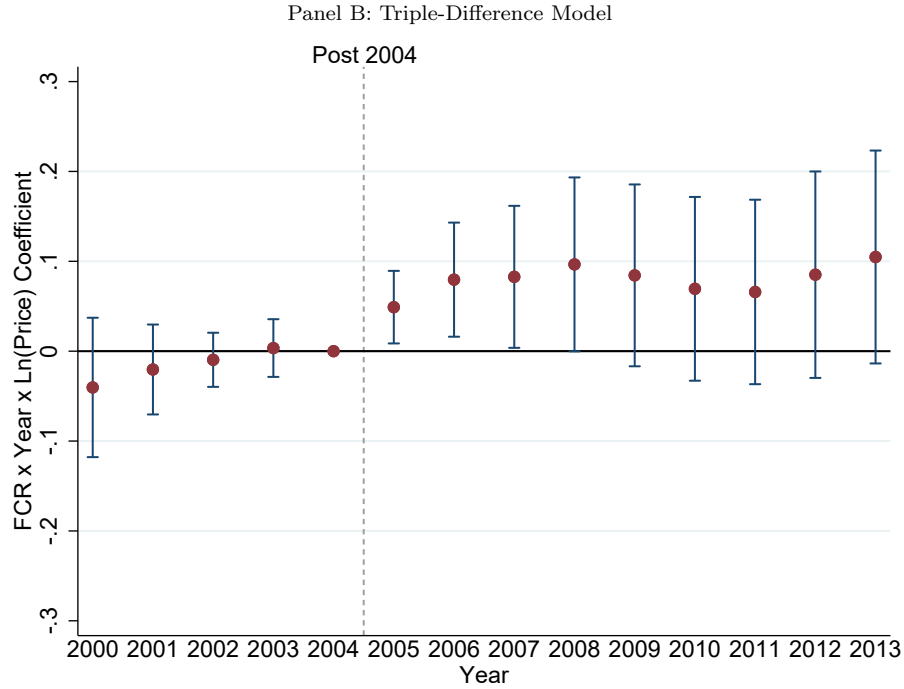
*Notes:* This table describes the sample selection process for our luminosity analyses. The sample is from 2000 to 2013. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. World commodity price data is from the United States Geological Survey and the World Bank. Luminosity data is from the National Centers for Environmental Information (NOAA).



**Figure IA2: Luminosity Effects in Event-Time Excluding Overlapping Extraction Areas**

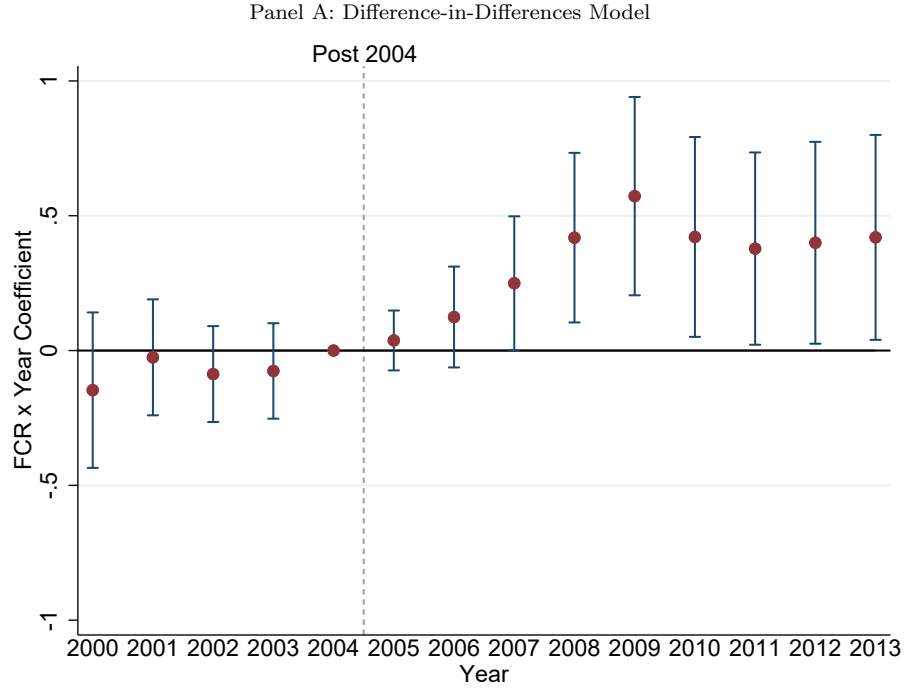


*Notes:* Panel A shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on nighttime luminosity. We estimate the model from Column (1) of Table 4 in the Manuscript but exclude extraction areas that overlap within a 10-kilometer radius, and replace the  $FCR \times Post\ 2004$  indicator with separate interactions for each of the years in our sample (except for 2004, which serves as the benchmark).

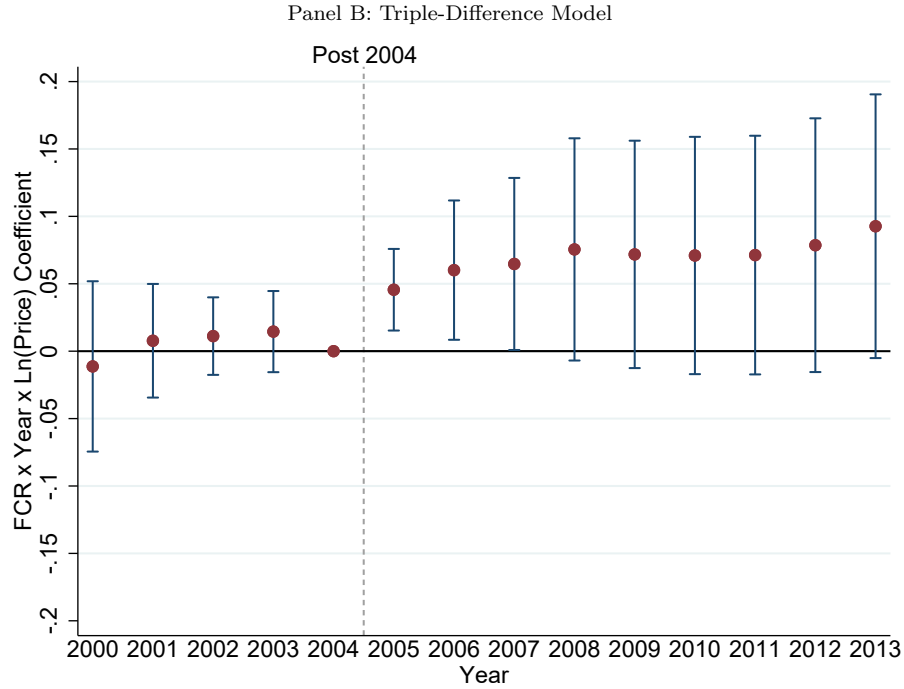


*Notes:* Panel B shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on the association between world commodity prices and nighttime luminosity. We estimate the model from Column (1) of Table 6 Panel B in the Manuscript but exclude extraction areas that overlap within a 10-kilometer radius, and replace the  $FCR \times Post\ 2004 \times Ln(Price)$  indicator with separate interactions for each of the years in our sample (except for 2004, which serves as the benchmark).

**Figure IA3: Luminosity Effects in Event-Time Keeping Only Main Minerals**

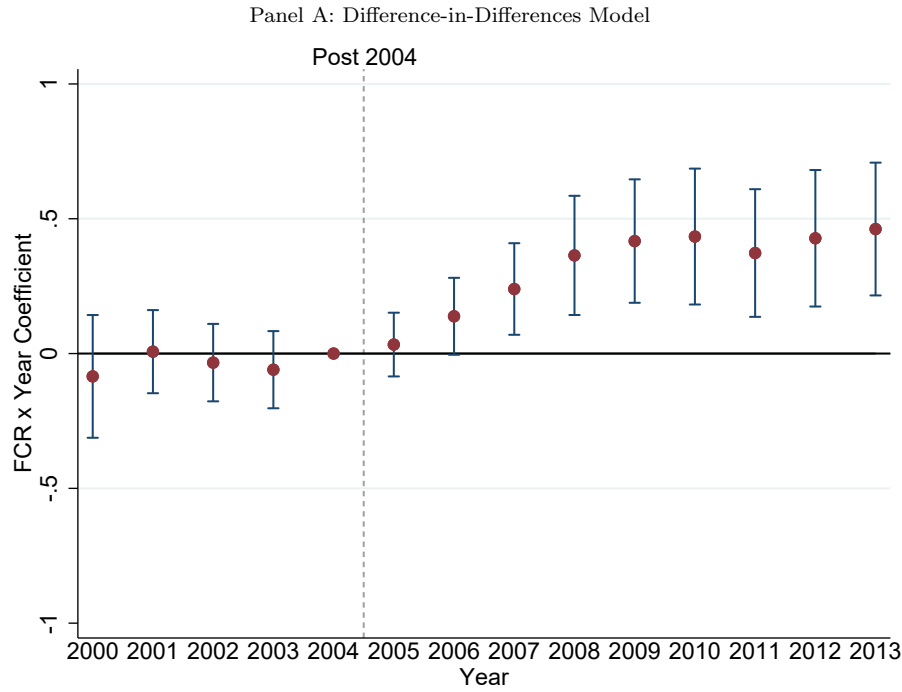


*Notes:* Panel A shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on nighttime luminosity. We estimate the model from Column (1) of Table 4 in the Manuscript but only keep the main mineral of each mine, and replace the  $FCR \times Post\ 2004$  indicator with separate interactions for each of the years in our sample (except for 2004, which serves as the benchmark).

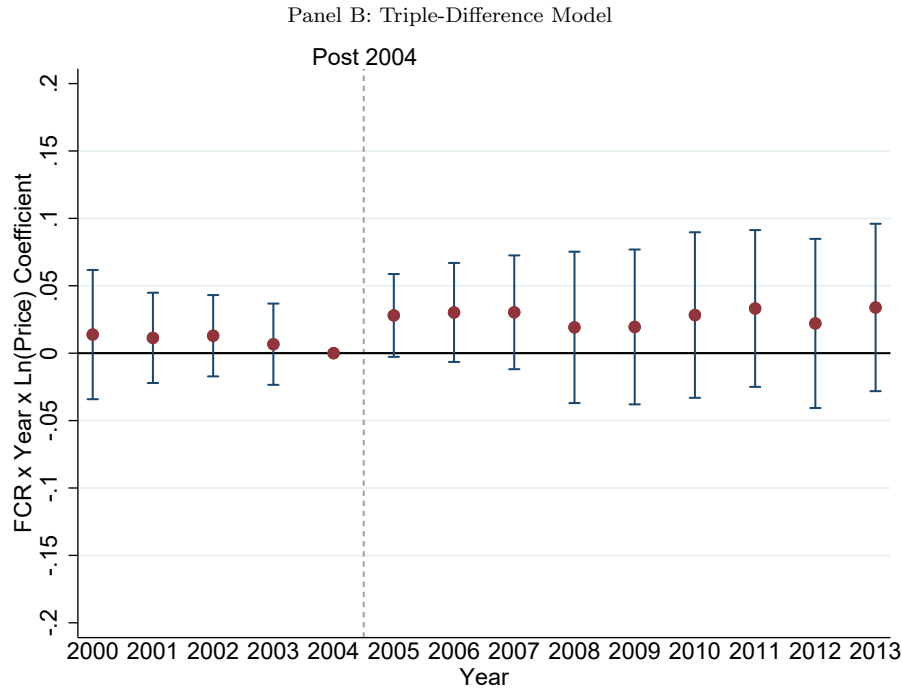


*Notes:* Panel B shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on the association between world commodity prices and nighttime luminosity. We estimate the model from Column (1) of Table 6 Panel B in the Manuscript but only keep the main mineral of each mine, and replace the  $FCR \times Post\ 2004 \times Ln(Price)$  indicator with separate interactions for each of the years in our sample (except for 2004, which serves as the benchmark).

**Figure IA4: Luminosity Effects in Event-Time Including Mines with Zero Reported Production**

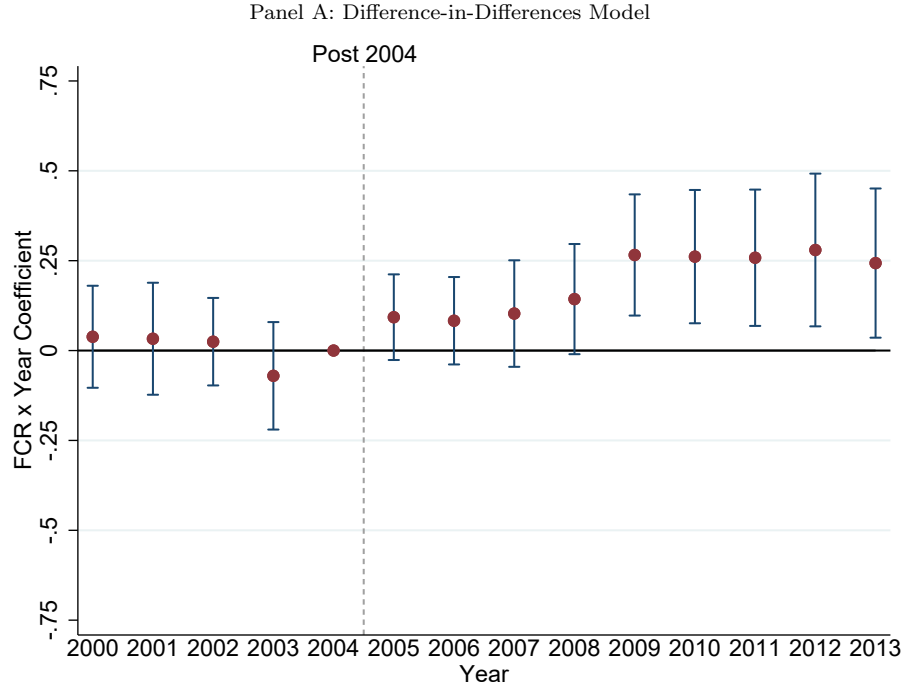


*Notes:* Panel A shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on nighttime luminosity. We estimate the model from Column (1) of Table 4 in the Manuscript but include mines with zero reported production, and replace the  $FCR \times Post\ 2004$  indicator with separate interactions for each of the years in our sample (except for 2004, which serves as the benchmark).

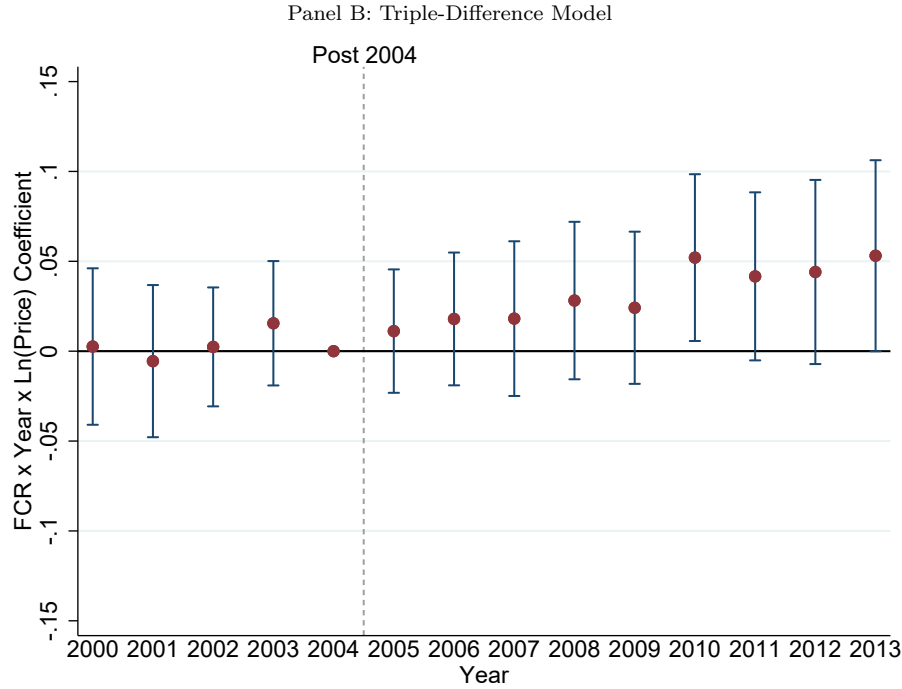


*Notes:* Panel B shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on the association between world commodity prices and nighttime luminosity. We estimate the model from Column (1) of Table 6 Panel B in the Manuscript but include mines with zero reported production, and replace the  $FCR \times Post\ 2004 \times Ln(Price)$  indicator with separate interactions for each of the years in our sample (except for 2004, which serves as the benchmark).

**Figure IA5: Treatment Effects in Event-Time using Ln(Luminosity) as Outcome Variable**



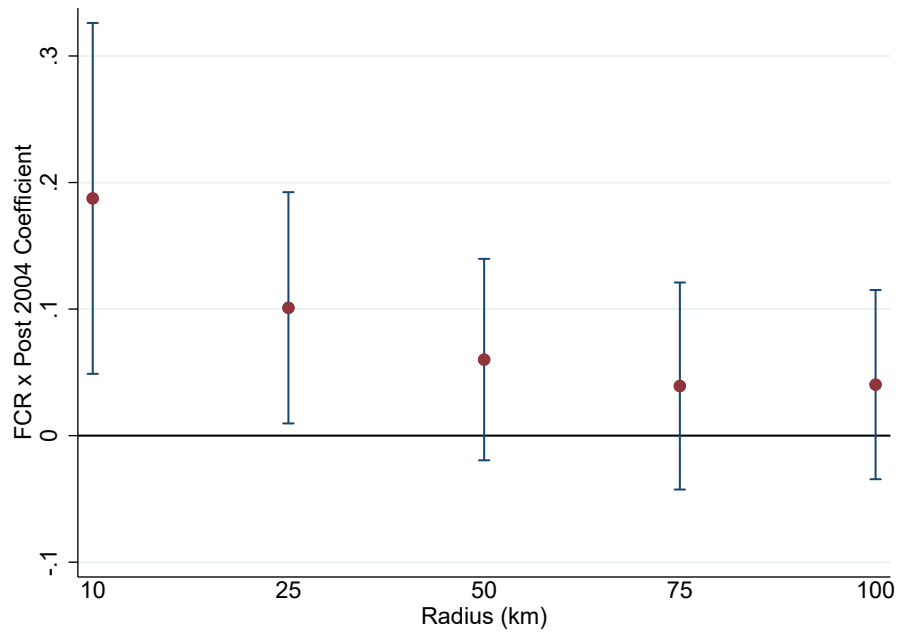
*Notes:* Panel A shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on nighttime luminosity. We estimate the model from Column (1) of Table 4 in the Manuscript but do not add 0.01 when log transforming *Luminosity*, and replace the  $FCR \times Post\ 2004$  indicator with separate interactions for each of the years in our sample (except for 2004, which serves as the benchmark).



*Notes:* Panel B shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on the association between world commodity prices and nighttime luminosity. We estimate the model from Column (1) of Table 6 Panel B in the Manuscript but do not add 0.01 when log transforming *Luminosity*, and replace the  $FCR \times Post\ 2004 \times Ln(Price)$  indicator with separate interactions for each of the years in our sample (except for 2004, which serves as the benchmark).

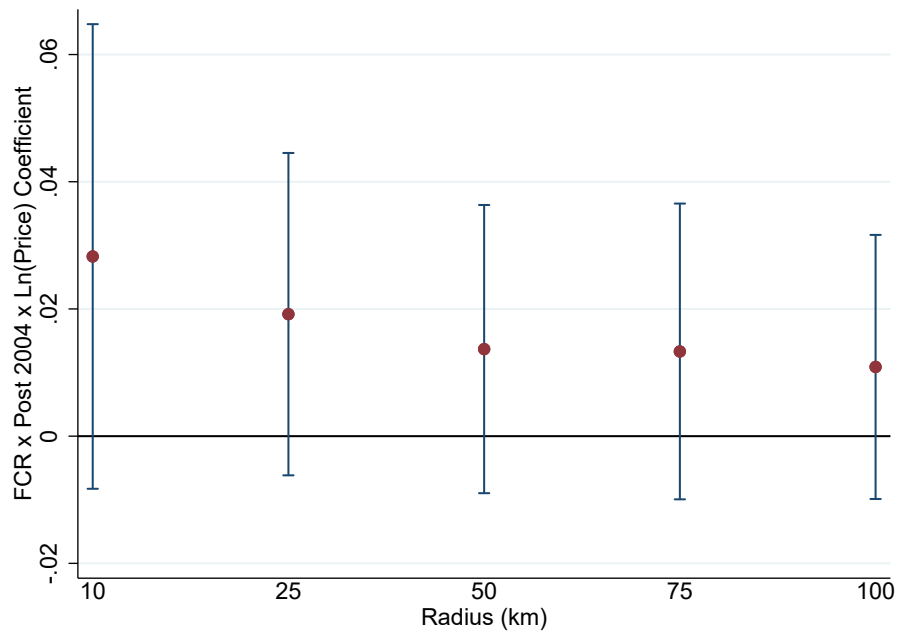
**Figure IA6: Spatial Diffusion of Treatment Effects using Ln(Luminosity) as Outcome Variable**

Panel A: Difference-in-Differences Model



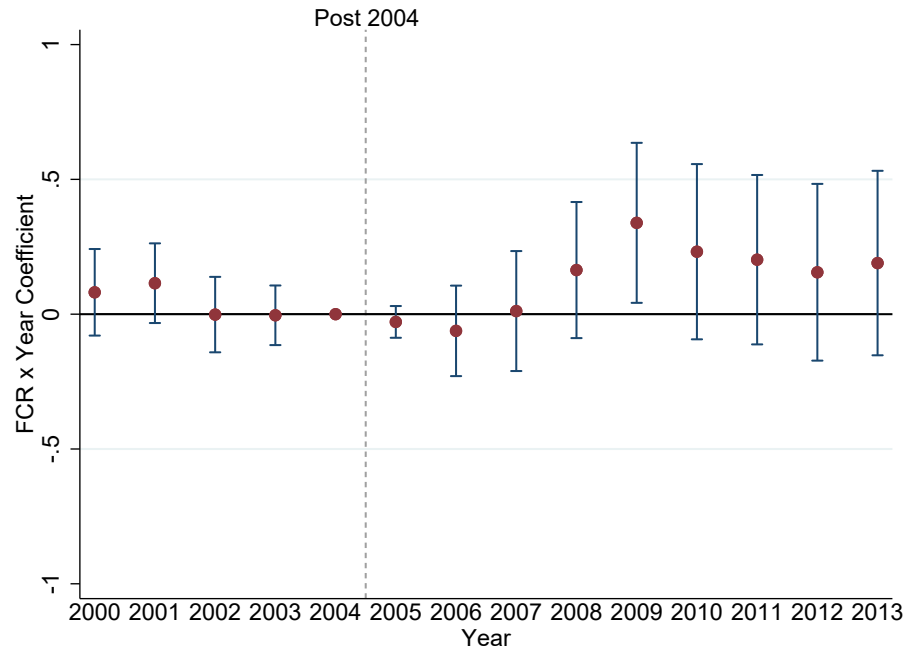
Notes: Panel A shows coefficient estimates of  $FCR \times Post\ 2004$  for cell areas with radii of 10km, 25km, 50km, 75km, and 100km, respectively. We estimate the model from Column (1) of Table 4 in the Manuscript but do not add 0.01 when log transforming *Luminosity*.

Panel B: Triple-Difference Model



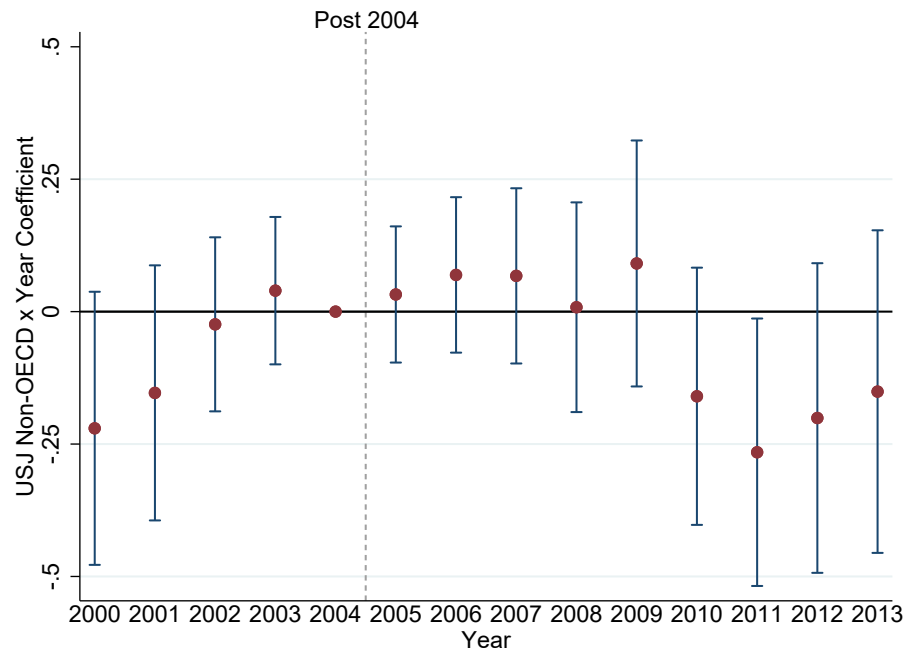
Notes: Panel B shows coefficient estimates of  $FCR \times Post\ 2004 \times Ln(Price)$  for cell areas with radii of 10km, 25km, 50km, 75km, and 100km, respectively. We estimate the model from Column (1) of Table 6 Panel B in the Manuscript but do not add 0.01 when log transforming *Luminosity*.

**Figure IA7: Luminosity Effects in Event-Time Excluding Gold**



*Notes:* This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on nighttime luminosity. We estimate the model from Column (1) of Table 4 in the Manuscript but exclude extraction areas around gold mines and replace the  $FCR \times Post\ 2004$  indicator with separate interactions for each of the years in our sample (except for 2004, which serves as the benchmark).

**Figure IA8: Placebo Difference-in-Differences Results in Event-Time**



*Notes:* This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on nighttime luminosity. We estimate the model from Column (4) of Table 4 in the Manuscript but replace the *USJ Non-OECD*  $\times$  *Post 2004* indicator with separate interactions for each of the years in our sample (except for 2004, which serves as the benchmark).

**Table IA3: Luminosity Effects Excluding Overlapping Extraction Areas**

**Panel A: Difference-in-Differences Regressions**

	Baseline	Sensitivity Analyses		
	(1)	(2)	(3)	(4)
Dependent Variable: $\ln(\text{Luminosity}(10) + 0.01)$	0-10 km Radius	1-10 km Radius	Within Region $\times$ Year	Placebo Test: USJ Non-OECD
$FCR \times \text{Post } 2004$	0.465*** (2.76)	0.449*** (2.69)	0.455*** (2.82)	
$USJ \text{ Non-OECD} \times \text{Post } 2004$				0.039 (0.25)
Fixed Effects:				
Property $\times$ Commodity	Yes	Yes	Yes	Yes
Region $\times$ Year	No	No	Yes	No
Commodity $\times$ Year	Yes	Yes	Yes	Yes
Property-Commodity-Year Observations	6,188	6,188	6,188	3,584

*Notes:* This table reports coefficient estimates of OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on nighttime luminosity. We exclude extraction areas that overlap within a 10-kilometer radius. We define all variables in Appendix A. We describe the sample selection in Table IA2. The sample is from 2000 to 2013. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. SEC filing data is from the S&P and Seek Edgar databases. Luminosity data is from the National Centers for Environmental Information (NOAA). We collect geographic segment-level data and financial data from Worldscope. T-statistics, reported in parentheses, are based on Conley (1999) standard errors allowing for spatial correlation within a 500km radius and for infinite serial correlation. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

**Panel B: Triple-Difference Regressions**

	Baseline	Sensitivity Analyses		
	(1)	(2)	(3)	(4)
Dependent Variable: $\ln(\text{Luminosity}(10) + 0.01)$	0-10 km Radius	1-10 km Radius	Within Region $\times$ Year	Placebo Test: USJ Non-OECD
$FCR \times \text{Post } 2004 \times \ln(\text{Price})$	0.091** (1.98)	0.093** (2.05)	0.086* (1.89)	
$FCR \times \ln(\text{Price})$	0.172 (0.32)	0.204 (0.39)	0.134 (0.25)	
$USJ \text{ Non-OECD} \times \text{Post } 2004 \times \ln(\text{Price})$				0.035 (0.78)
$USJ \text{ Non-OECD} \times \ln(\text{Price})$				-0.971*** (-3.59)
Fixed Effects:				
Property $\times$ Commodity	Yes	Yes	Yes	Yes
Region $\times$ Year	No	No	Yes	No
Commodity $\times$ Year	Yes	Yes	Yes	Yes
FCR $\times$ Year	Yes	Yes	Yes	Yes
Property-Commodity-Year Observations	4,760	4,760	4,760	2,590

*Notes:* This table reports coefficient estimates of OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on the association between world commodity prices and nighttime luminosity. We exclude extraction areas that overlap within a 10-kilometer radius. We define all variables in Appendix A. We describe the sample selection in Table IA2. The sample is from 2000 to 2013. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. SEC filing data is from the S&P and Seek Edgar databases. World commodity price data is from the United States Geological Survey and the World Bank. Luminosity data is from the National Centers for Environmental Information (NOAA). We collect geographic segment-level data and financial data from Worldscope. T-statistics, reported in parentheses, are based on Conley (1999) standard errors allowing for spatial correlation within a 500km radius and for infinite serial correlation. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.



**Table IA4: Luminosity Effects Keeping Only Main Minerals**

**Panel A: Difference-in-Differences Regressions**

	Baseline	Sensitivity Analyses		
	(1)	(2)	(3)	(4)
Dependent Variable: $\ln(\text{Luminosity (10)} + 0.01)$	0-10 km Radius	1-10 km Radius	Within Region $\times$ Year	Placebo Test: USJ Non-OECD
$\text{FCR} \times \text{Post } 2004$	0.403*** (2.71)	0.392*** (2.66)	0.410*** (2.96)	
$\text{USJ Non-OECD} \times \text{Post } 2004$				-0.177 (-1.51)
Fixed Effects:				
Property $\times$ Commodity	Yes	Yes	Yes	Yes
Region $\times$ Year	No	No	Yes	No
Commodity $\times$ Year	Yes	Yes	Yes	Yes
Property-Commodity-Year Observations	8,050	8,050	8,050	5,222

*Notes:* This table reports coefficient estimates of OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on nighttime luminosity. We only keep the main mineral of each mine, determined by maximum production value over the sample period. We define all variables in Appendix A. We describe the sample selection in Table IA2. The sample is from 2000 to 2013. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. SEC filing data is from the S&P and Seek Edgar databases. Luminosity data is from the National Centers for Environmental Information (NOAA). We collect geographic segment-level data and financial data from Worldscope. T-statistics, reported in parentheses, are based on Conley (1999) standard errors allowing for spatial correlation within a 500km radius and for infinite serial correlation. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

**Panel B: Triple-Difference Regressions**

	Baseline	Sensitivity Analyses		
	(1)	(2)	(3)	(4)
Dependent Variable: $\ln(\text{Luminosity (10)} + 0.01)$	0-10 km Radius	1-10 km Radius	Within Region $\times$ Year	Placebo Test: USJ Non-OECD
$\text{FCR} \times \text{Post } 2004 \times \ln(\text{Price})$	0.061* (1.65)	0.062* (1.70)	0.048 (1.36)	
$\text{FCR} \times \ln(\text{Price})$	0.394 (1.17)	0.420 (1.29)	0.352 (1.10)	
$\text{USJ Non-OECD} \times \text{Post } 2004 \times \ln(\text{Price})$				0.009 (0.33)
$\text{USJ Non-OECD} \times \ln(\text{Price})$				-0.520** (-2.54)
Fixed Effects:				
Property $\times$ Commodity	Yes	Yes	Yes	Yes
Region $\times$ Year	No	No	Yes	No
Commodity $\times$ Year	Yes	Yes	Yes	Yes
FCR $\times$ Year	Yes	Yes	Yes	Yes
Property-Commodity-Year Observations	6,622	6,622	6,622	4,228

*Notes:* This table reports coefficient estimates of OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on the association between world commodity prices and nighttime luminosity. We only keep the main mineral of each mine, determined by maximum production value over the sample period. We define all variables in Appendix A. We describe the sample selection in Table IA2. The sample is from 2000 to 2013. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. SEC filing data is from the S&P and Seek Edgar databases. World commodity price data is from the United States Geological Survey and the World Bank. Luminosity data is from the National Centers for Environmental Information (NOAA). We collect geographic segment-level data and financial data from Worldscope. T-statistics, reported in parentheses, are based on Conley (1999) standard errors allowing for spatial correlation within a 500km radius and for infinite serial correlation. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

**Table IA5: Luminosity Effects Including Mines with Zero Reported Production**

**Panel A: Difference-in-Differences Regressions**

	Baseline	Sensitivity Analyses		
	(1) 0-10 km Radius	(2) 1-10 km Radius	(3) Within Region $\times$ Year	(4) Placebo Test: USJ Non-OECD
Dependent Variable: $\text{Ln}(\text{Luminosity (10)} + 0.01)$				
$\text{FCR} \times \text{Post 2004}$	0.355*** (3.78)	0.346*** (3.72)	0.363*** (3.85)	
$\text{USJ Non-OECD} \times \text{Post 2004}$				-0.058 (-1.00)
Fixed Effects:				
Property $\times$ Commodity	Yes	Yes	Yes	Yes
Region $\times$ Year	No	No	Yes	No
Commodity $\times$ Year	Yes	Yes	Yes	Yes
Property-Commodity-Year Observations	49,619	49,619	49,059	44,887

*Notes:* This table reports coefficient estimates of OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on nighttime luminosity including mines with zero reported production. We define all variables in Appendix A. We describe the sample selection in Table IA2. The sample is from 2000 to 2013. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. SEC filing data is from the S&P and Seek Edgar databases. Luminosity data is from the National Centers for Environmental Information (NOAA). We collect geographic segment-level data and financial data from Worldscope. T-statistics, reported in parentheses, are based on Conley (1999) standard errors allowing for spatial correlation within a 500km radius and for infinite serial correlation. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

**Panel B: Triple-Difference Regressions**

	Baseline	Sensitivity Analyses		
	(1) 0-10 km Radius	(2) 1-10 km Radius	(3) Within Region $\times$ Year	(4) Placebo Test: USJ Non-OECD
Dependent Variable: $\text{Ln}(\text{Luminosity (10)} + 0.01)$				
$\text{FCR} \times \text{Post 2004} \times \text{Ln}(\text{Price})$	0.014 (0.57)	0.015 (0.65)	0.017 (0.73)	
$\text{FCR} \times \text{Ln}(\text{Price})$	0.298** (2.01)	0.301** (2.07)	0.293** (2.03)	
$\text{USJ Non-OECD} \times \text{Post 2004} \times \text{Ln}(\text{Price})$				0.000 (0.01)
$\text{USJ Non-OECD} \times \text{Ln}(\text{Price})$				-0.174 (-1.46)
Fixed Effects:				
Property $\times$ Commodity	Yes	Yes	Yes	Yes
Region $\times$ Year	No	No	Yes	No
Commodity $\times$ Year	Yes	Yes	Yes	Yes
FCR $\times$ Year	Yes	Yes	Yes	Yes
Property-Commodity-Year Observations	44,299	44,299	43,739	40,155

*Notes:* This table reports coefficient estimates of OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on the association between world commodity prices and nighttime luminosity including mines with zero reported production. We define all variables in Appendix A. We describe the sample selection in Table IA2. The sample is from 2000 to 2013. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. SEC filing data is from the S&P and Seek Edgar databases. World commodity price data is from the United States Geological Survey and the World Bank. Luminosity data is from the National Centers for Environmental Information (NOAA). We collect geographic segment-level data and financial data from Worldscope. T-statistics, reported in parentheses, are based on Conley (1999) standard errors allowing for spatial correlation within a 500km radius and for infinite serial correlation. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

**Table IA6: Jackknife Procedure Excluding Individual Minerals**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable: $\ln(\text{Luminosity (10)} + 0.01)$	Baseline	Excluding Aluminum	Excluding Chromite	Excluding Coal	Excluding Cobalt	Excluding Copper	Excluding Diamond	Excluding Gold	Excluding Iron	Excluding Lead
$FCR \times \text{Post } 2004$	0.338** (2.57)	0.338** (2.55)	0.341** (2.47)	0.448*** (2.62)	0.346*** (2.58)	0.304** (2.23)	0.364*** (2.79)	0.096 (0.83)	0.344** (2.57)	0.356*** (2.65)
Fixed Effects:										
Property $\times$ Commodity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region $\times$ Year	No	No	No	No	No	No	No	No	No	No
Commodity $\times$ Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Property-Commodity-Year Observations	10,122	10,052	9,870	8,694	9,814	9,100	8,932	7,742	9,856	10,024

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable: $\ln(\text{Luminosity (10)} + 0.01)$	Excluding Manganese	Excluding Nickel	Excluding Oil	Excluding Phosphate	Excluding Platinum	Excluding Silver	Excluding Tantalum	Excluding Vanadium	Excluding Zinc	Excluding Zircon
$FCR \times \text{Post } 2004$	0.340** (2.54)	0.310** (2.36)	0.353** (2.57)	0.338** (2.57)	0.338** (2.54)	0.358*** (2.72)	0.338** (2.57)	0.338** (2.55)	0.357*** (2.63)	0.372*** (2.82)
Fixed Effects:										
Property $\times$ Commodity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region $\times$ Year	No	No	No	No	No	No	No	No	No	No
Commodity $\times$ Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Property-Commodity-Year Observations	9,968	9,618	8,736	10,066	9,576	9,954	10,080	10,080	9,968	10,066

*Notes:* This table reports coefficient estimates of OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on nighttime luminosity. We estimate the model from Column (1) of Table 4 in the Manuscript, but separately exclude individual minerals. We define all variables in Appendix A. We describe the sample selection in Table IA2 of the Internet Appendix. The sample is from 2000 to 2013. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. SEC filing data is from the S&P and Seek Edgar databases. Luminosity data is from the National Centers for Environmental Information (NOAA). We collect geographic segment-level data and financial data from Worldscope. T-statistics, reported in parentheses, are based on Conley (1999) standard errors allowing for spatial correlation within a 500km radius and for infinite serial correlation. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

**Table IA7: Survey Respondents in Extraction Areas by Country and Round**

	All Respondents	Round 1 1999/2000/2001	Round 2 2002/2003/2004	Round 3 2005/2006	Round 4 2008/2009	Round 5 2011/2012/2013	Round 6 2014/2015
Algeria	274	.	.	.	.	158	116
Botswana	5,178	767	807	910	916	915	863
Burkina Faso	2,047	.	.	.	600	637	810
Burundi	509	.	.	.	.	230	279
Egypt	644	.	.	.	.	400	244
Gabon	277	.	.	.	.	.	277
Ghana	5,478	1,190	575	519	619	1,339	1,236
Guinea	1,628	.	.	.	.	809	819
Ivory Coast	787	.	.	.	.	330	457
Kenya	586	.	180	71	63	122	150
Lesotho	3,963	613	664	502	702	693	789
Liberia	868	.	.	.	277	274	317
Madagascar	619	.	.	146	101	119	253
Malawi	79	16	15	14	6	13	15
Mali	1,438	365	244	198	171	230	230
Morocco	418	.	.	.	.	224	194
Mozambique	872	.	74	145	169	223	261
Namibia	1,803	306	263	281	297	329	327
Niger	311	.	.	.	.	194	117
Nigeria	1,995	427	367	412	244	275	270
Senegal	90	.	11	16	22	12	29
Sierra Leone	2,163	.	.	.	.	1,153	1,010
South Africa	7,827	1,128	1,303	1,290	1,298	1,340	1,468
Sudan	43	.	.	.	.	15	28
Swaziland	2,125	.	.	.	.	1,038	1,087
Tanzania	2,194	530	195	171	273	472	553
Togo	152	.	.	.	.	81	71
Tunisia	799	.	.	.	.	402	397
Uganda	2,349	353	487	352	367	408	382
Zambia	2,558	375	492	388	423	405	475
Zimbabwe	7,555	932	808	839	852	2,216	1,908
Total	57,629	7,002	6,485	6,254	7,400	15,056	15,432

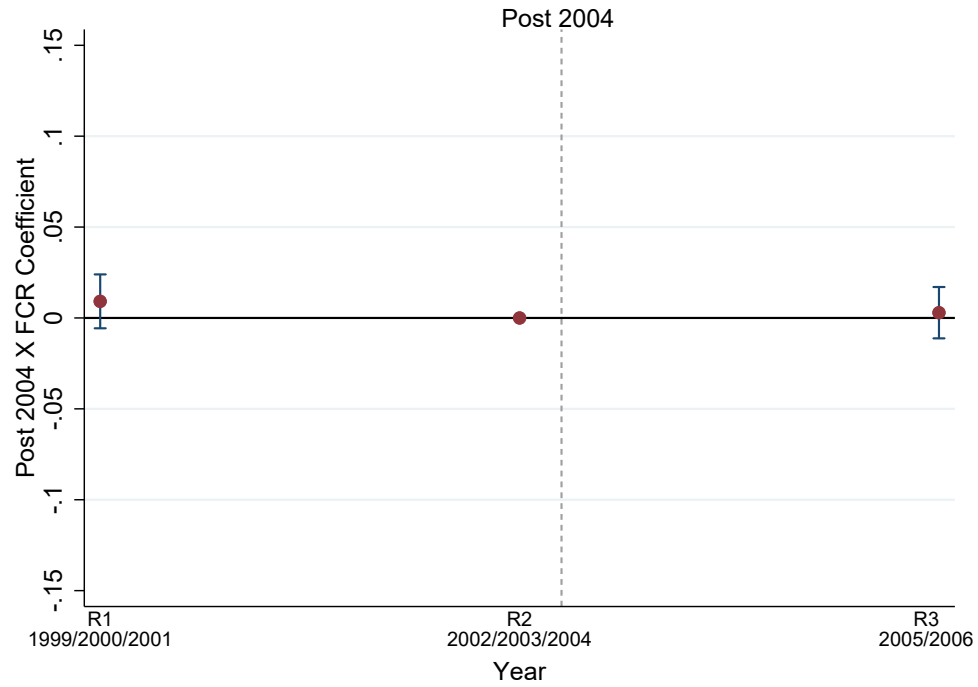
*Notes:* This table presents the number of Afrobarometer survey respondents by country and round. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. We collect survey data from rounds 1 to 6 of the Afrobarometer.

**Table IA8: Perception Results Excluding Afrobarometer Survey Round 1**

	(1) Corrupt Government	(2) Satisfied with Local Government
<i>FCR Exposure</i> $\times$ <i>Post 2004</i>	-0.068*** (-2.84)	0.080** (2.44)
<i>FCR Exposure</i>	0.033 (1.45)	-0.044 (-1.37)
Controls:		
<i>Female</i>	-0.023*** (-5.62)	0.010** (2.45)
<i>Urban</i>	0.055*** (8.73)	-0.062*** (-8.08)
<i>Ln(Age)</i>	-0.024*** (-3.93)	0.056*** (8.48)
Fixed Effects:		
Region $\times$ Year	Yes	Yes
Mineral	Yes	Yes
Standard Error Clusters:		
Village	4,205	4,019
Adjusted R-Squared	0.028	0.061
Observations	49,481	47,944

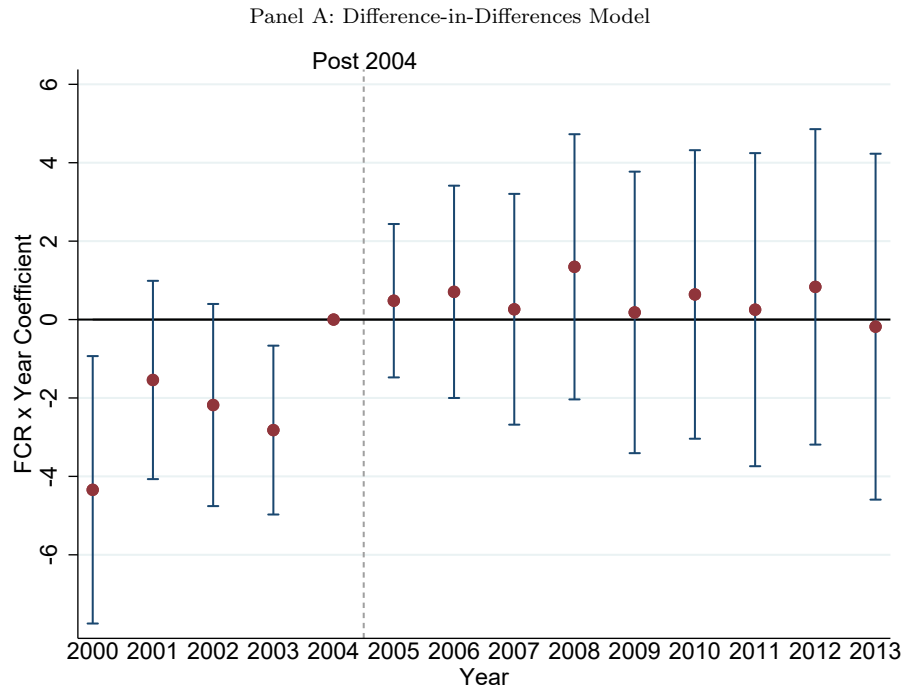
*Notes:* This table reports coefficient estimates of OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on the perceived corruption of government officials and the perceived satisfaction with local governments, excluding Afrobarometer survey round 1. We define all variables in Appendix A. The sample is from 2002 to 2015. Mine-level data is from the SNL Metals and Mining Database and oil-well data is from Enverus International. SEC filing data is from the S&P and Seek Edgar databases. We collect geographic segment-level data and financial data from Worldscope. We collect survey data from rounds 1 to 6 of the Afrobarometer. T-statistics, reported in parentheses, are based on standard errors clustered at the village level. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

**Figure IA9: Mining Occupation Effects in Event-Time**

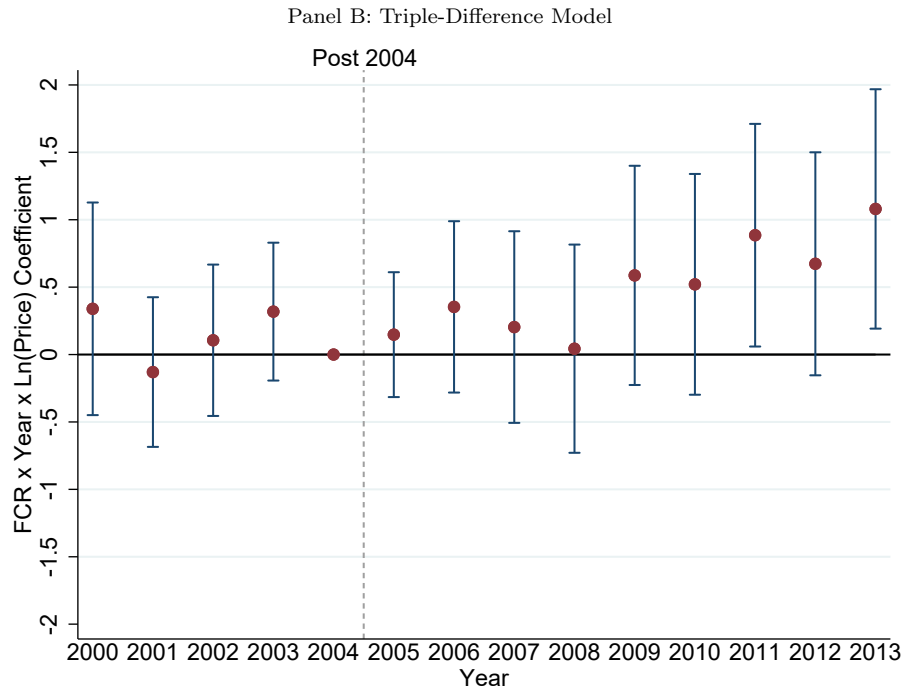


*Notes:* This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on mining-related employment in mining areas. We estimate the model from Column (2) of Table IA9 but replace the  $FCR \times Post\ 2004$  indicator with separate interactions for each survey round in our sample (except for Round 2, which serves as the benchmark).

Figure IA10: Mineral Production Effects in Event-Time

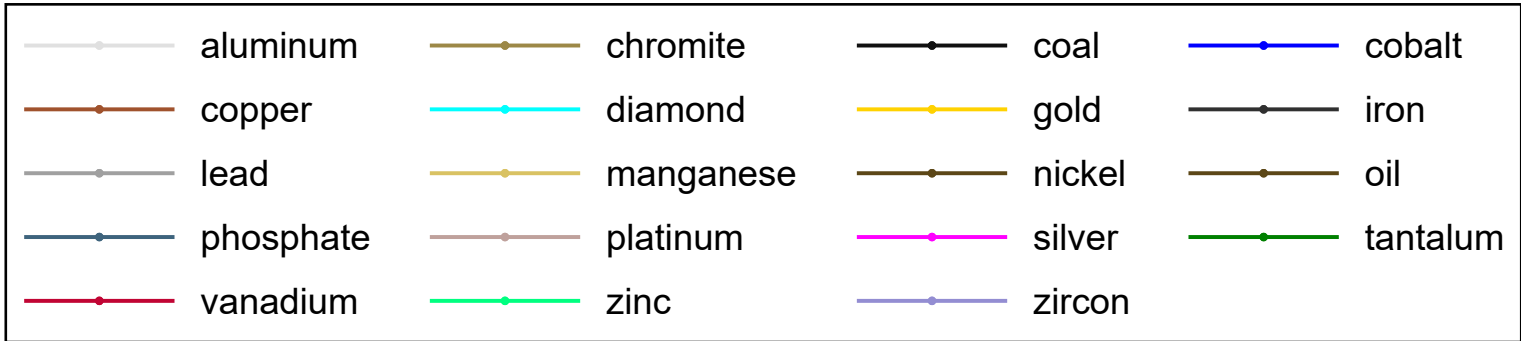


Notes: Panel A shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on local property-level production. We estimate the model from Column (1) of Table IA10 but replace the  $FCR \times Post\ 2004$  indicator with separate interactions for each of the years in our sample (except for 2004, which serves as the benchmark).



Notes: Panel B shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on the association between world commodity prices and local property-level production. We estimate the model from Column (2) of Table IA10 but replace the  $FCR \times Post\ 2004 \times Ln(Price)$  indicator with separate interactions for each of the years in our sample (except for 2004, which serves as the benchmark).

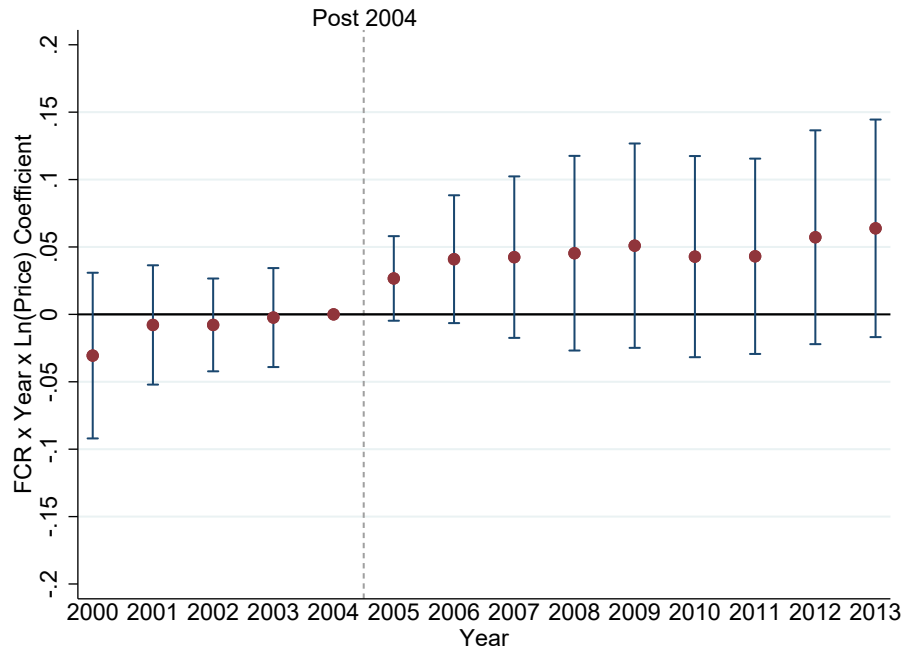
20



*Notes:* This figure shows commodity prices from 2000 to 2013. All prices are indexed to 2004. World commodity price data is from the United States Geological Survey and the World Bank.



**Figure IA12: Luminosity Effects in Event-Time with  
Region  $\times$  Year Fixed Effects**



*Notes:* This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on the association between world commodity prices and nighttime luminosity. We estimate the model from Column (3) of Table 6 Panel B in the Manuscript but replace the  $FCR \times Post\ 2004 \times Ln(Price)$  indicator with separate interactions for each of the years in our sample (except for 2004, which serves as the benchmark).

**Table IA9: Effect of Foreign Corruption Regulation on Mining Occupation**

	(1) Without Region $\times$ Round FE	(2) With Region $\times$ Round FE
Dependent Variable: Fraction of Miners		
$FCR \times Post\ 2004$	0.003 (0.41)	-0.002 (-0.30)
Fixed Effects:		
Property $\times$ Commodity	Yes	Yes
Region $\times$ Round	No	Yes
Commodity $\times$ Round	Yes	Yes
Property-Commodity-Round Observations	1,413	1,413

*Notes:* This table reports coefficient estimates of OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on mining-related employment in mining areas. We define all variables in Appendix A. We collect survey data from rounds 1 to 6 of the Afrobarometer. Mine-level data is from the SNL Metals. SEC filing data is from the S&P and Seek Edgar databases. We collect geographic segment-level data and financial data from Worldscope. T-statistics, reported in parentheses, are based on Conley (1999) standard errors allowing for spatial correlation within a 500km radius and for infinite serial correlation. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

**Table IA10: Effect of Foreign Corruption Regulation on Mineral Production**

Dependent Variable:	(1) Ln(Production+0.01)	(2) Ln(Production+0.01)
$FCR \times Post\ 2004$	4.364** (2.49)	
$FCR \times Post\ 2004 \times Ln(Price)$		0.381 (1.38)
$FCR \times Ln(Price)$		1.306 (0.59)
Fixed Effects:		
Property $\times$ Commodity	Yes	Yes
Region $\times$ Year	No	No
Commodity $\times$ Year	Yes	Yes
FCR $\times$ Year	No	Yes
Property-Commodity-Year Observations	3,234	7,371

*Notes:* This table reports coefficient estimates of OLS regressions estimating the effect of the post-2004 increase in FCPA enforcement on local property-level production. We define all variables in Appendix A. The sample is from 2000 to 2013. We limit our sample to mines with positive reported production in 2004. Mine-level data is from the SNL Metals and Mining Database, and oil-well data is from Enverus International. SEC filing data is from the S&P and Seek Edgar databases. Luminosity data is from the National Centers for Environmental Information (NOAA). We collect geographic segment-level data and financial data from Worldscope. T-statistics, reported in parentheses, are based on Conley (1999) standard errors allowing for spatial correlation within a 500km radius and for infinite serial correlation. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.