Online Appendix: Mining and local corruption in Africa

A Overview of the Online Appendix

This Appendix contains robustness tests and additional analyses discussed, but not reported in tables, in the paper, as well as descriptive statistics and information on data and particular measures. The sequence of the following sections follows the sequence in which the various tests are discussed in the data and empirical sections of the paper.

Section A.1 maps the mines and survey clusters and specifies the number of individuals, by country and Afrobarometer Wave, included in the sample. The section also lists the minerals for which we have mining data, and presents descriptive statistics for our core variables. Section A.2 presents results for closely related treatments, drawing on alternative data sources, namely measures on the presence of alluvial diamond mines, USGS mines, and oil deposits. Section A.3 shows placebo tests on measures of national corruption, whereas the extensive Section A.4 contains numerous alternative tests probing the sensitivity of our main analysis. Section A.5 reports tests employing a different unit of analysis, namely Enumeration Areas (rather than individuals). Section A.6 presents tests where we investigate whether high- and low-production/value mines have differential effects on corruption, and also, for instance, tests where conditioning on the number of already active mines affects our results. Section A.7 provides an extended discussion of tests on the sub-sample of South Africa, while Section A.8 reports tests for other sub-samples. The discussion of our instrumental variable models and results appear in Section A.9. Section A.10 provides a detailed discussion of the nighttime light data and measures that are used for exploring the proposed mechanisms. This section also reports tables with the various results relevant for testing the four mechanisms that we discuss in the paper. Finally, section A.11 presents a tentative investigation of whether our results scale up to the national level, by investigating correlations between national level aggregates of our mining data and different corruption measures.

The overall conclusion emanating from this battery of additional tests and analyses is that there is fairly strong evidence for a "local resource curse". Our main result does not seem to be driven by particular sub-samples, endogeneity or other sources or confounding. It also seems to be more comprehensive than our baseline results suggest, as the mining-corruption link appears for other measures of corruption, such as bribes to tax officials (despite less extensive data coverage). Further evidence in line with the "local resource curse" is detectable also when using conceptually related right-hand side variables, such as onshore oil deposits and artisanal (diamond) mines.

A.1 Data characteristics and descriptive statistics

Figure A.1 maps the 604 identified African industrial mines, and our 33-country sample allows matching 496 mines to survey respondents. The large-scale industrial mines from the RMD dataset (SNL Metals and Mining, 2014) that are included in our sample are reported to produce one of the following (as its main mineral):[1] Silver, Aluminum (Bauxite), Gold, Coal, Chromite, Copper, Diamonds, Iron, Manganese, Nickel, Phosphate, Lead, Platinum, Antimony, Tin, Tantalum, Titanium, Uranium, Vanadium, Zinc.

After that, Figure A.2 shows the survey cluster locations in our sample, and Table A.1 breaks down the survey respondents by country and Afrobarometer wave (Afrobarometer Data, N.d.). Finally, Table A.2 shows descriptive statistics for all our core variables, calculated over the observations included in Model 1 in Table 1 of the paper.

[1] "Mineral" is here used as shorthand for "Metal, mineral or rock".

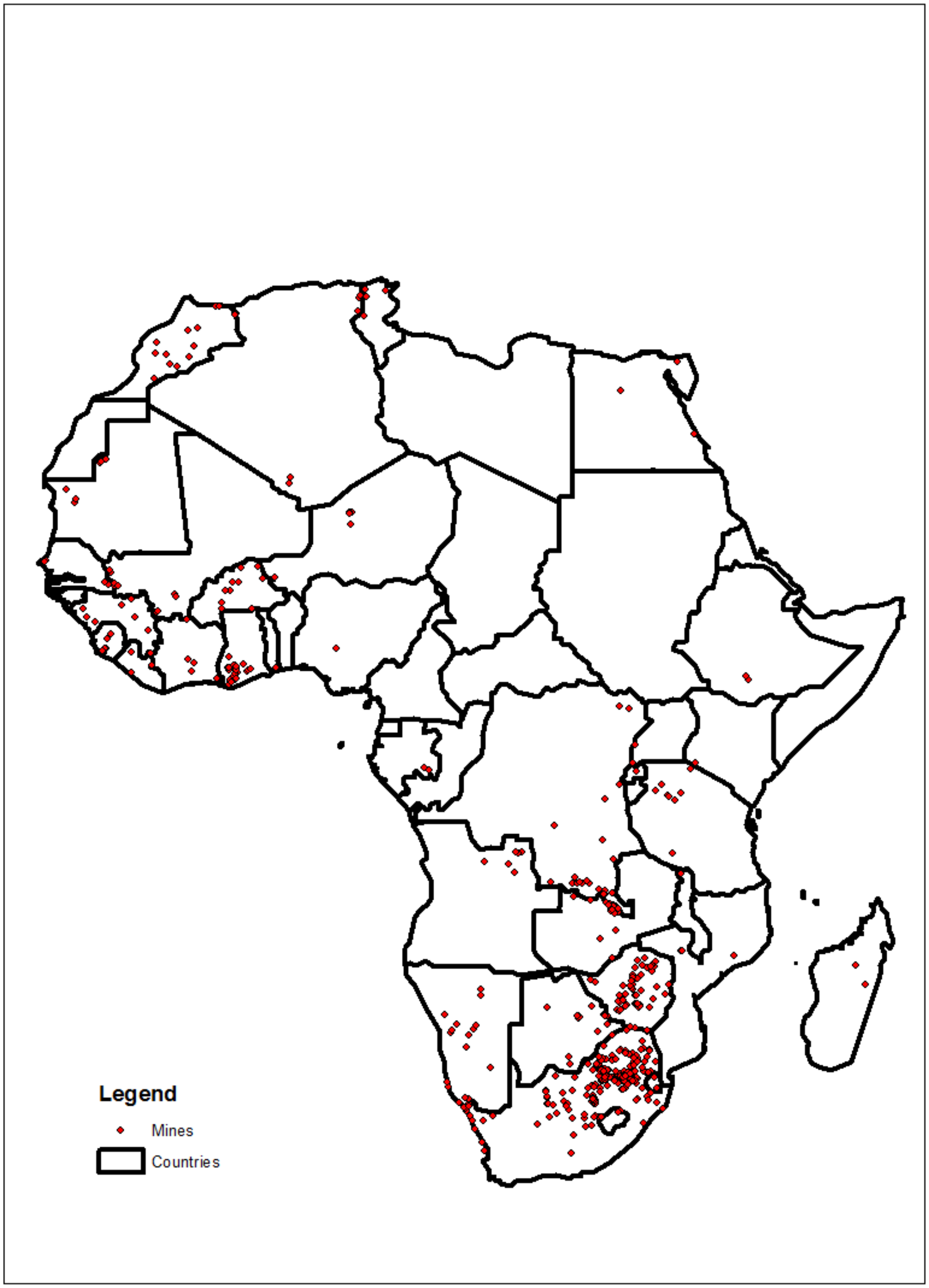

Figure A.1: Localization of industrial mines in Africa

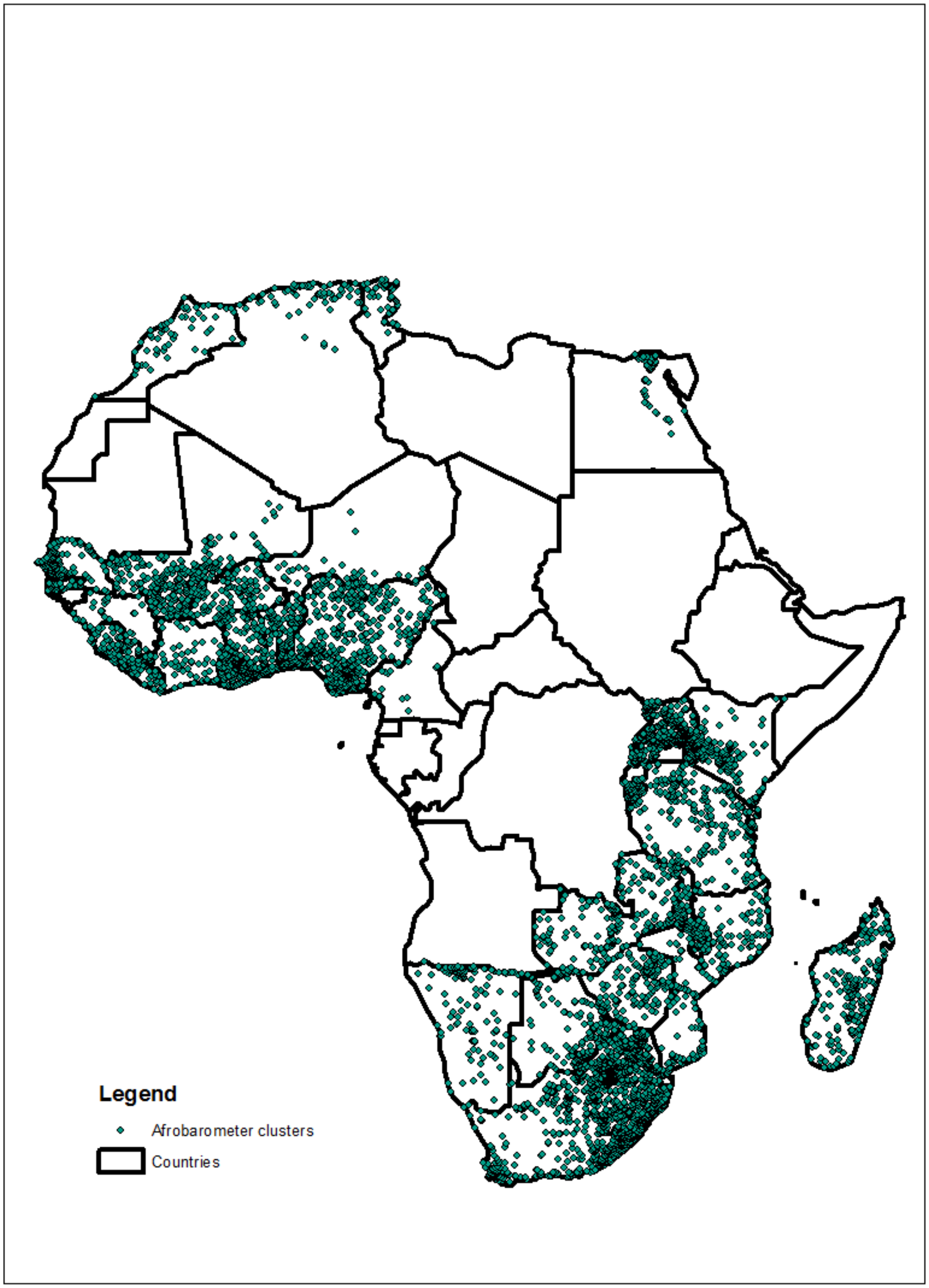

Figure A.2: Afrobarometer survey clusters in 33 African countries

Table A.1: Numbers of individuals in our sample, broken down by country and Afrobarometer wave

	Afrobarometer wave					
Country	2	2.5	3	4	5	Total
Algeria	0	0	0	0	887	887
Benin	0	0	1,165	1,189	881	3,235
Botswana	1,013	0	1,121	1,156	607	3,897
Burkina Faso	0	0	0	1,081	576	1,657
Burundi	0	0	0	0	728	728
Cameroon	0	0	0	0	235	235
Cape Verde	0	0	708	561	626	1,895
Cote D'Ivoire	0	0	0	0	966	966
Egypt	0	0	0	0	860	860
Ghana	799	0	1,016	1,068	1,053	3,936
Guinea	0	0	0	0	473	473
Kenya	0	0	1,259	1,051	2,006	4,316
Lesotho	1,148	0	1,153	1,112	1,022	4,435
Liberia	0	0	0	1,146	671	1,817
Madagascar	0	0	1,304	1,327	721	3,352
Malawi	1,040	0	1,132	1,136	2,001	5,309
Mali	0	0	1,117	1,216	340	2,673
Mauritius	0	0	0	0	1,057	1,057
Morocco	0	0	0	0	803	803
Mozambique	761	0	1,079	836	1,127	3,803
Namibia	544	0	1,071	1,194	342	3,151
Niger	0	0	0	0	593	593
Nigeria	1,989	0	2,010	2,255	1,030	7,284
Senegal	0	0	968	1,090	938	2,996
Sierra Leone	0	0	0	0	506	506
South Africa	1,931	2,268	2,239	2,202	1,926	10,566
Swaziland	0	0	0	0	207	207
Tanzania	1,109	0	979	1,189	1,100	4,377
Togo	0	0	0	0	252	252
Tunisia	0	0	0	0	465	465
Uganda	1,918	0	2,307	2,324	1,874	8,423
Zambia	1,091	0	1,158	1,145	914	4,308
Zimbabwe	719	0	987	719	875	3,300
Total	14,062	2,268	22,773	24,997	28,662	92,762

Table A.2: Descriptive statistics calculated for the 33-country sample of Model 1, Table 1.

	Mean	SD
Mining variables		
Kilometers	207.888	(202.537)
Active 50 km	0.157	(0.363)
Inactive 50 km	0.014	(0.117)
Active 25 km	0.080	(0.271)
Inactive 25 km	0.007	(0.083)
Dependent variables: Paid a bribe last year		
– to the Police	0.225	(0.657)
– for a Permit	0.227	(0.624)
Perception of corruption		
Local councilors	1.306	(0.847)
Police	1.607	(0.890)
Control variables		
Urban	0.427	(0.495)
Age	36.658	(14.622)
Female	0.498	(0.500)
Education	3.278	(2.019)
N	92762	

A.2 Diamond mines, USGS mines, and oil extraction

A.2.1 Using data on diamond mines and USGS mines to investigate artisanal mining and corruption

As we discuss in the paper, the RMD dataset that we use for our main analysis covers industrial mining well, but excludes some crucial parts of the African mining sector. Notably, it does not cover artisanal mines, which are widespread in Africa. However, much of the diamond mining that has been fingered as a culprit in both underdevelopment and conflict in Africa (the "diamond curse", e.g., Lujala, Gleditsch and Gilmore, 2005) consists in artisanal mining. While we do not have a comprehensive dataset on artisanal mines, we do have data on diamond mines from Gilmore et al. (2005), comprising spatial data on the location of diamond deposits in Africa. Unfortunately, we can not employ our preferred difference-in-differences tests when using these data, since they do not contain the relevant information on active vs. inactive mines.

Still, Table A.3 shows the correlations between diamond mines and local corruption from models where we otherwise employ the same type of spatial matching on mines and Afrobarometer respondents, and set-up (50km buffer zones), as in our main analysis. These results show basically the same patterns as our main models, namely a particularly strong relationship between having a diamond mine in the local area and the number of police bribes. The correlations are also positive and weakly significant ($p < 0.10$) for permit bribes and perceived police corruption, while it has the wrong sign (but is statistically insignificant) for perceived local councilor corruption. As for our main models, an argument can be made against including individual-level control variables; diamond mining may have effects on, for example, education, thus inducing post-treatment bias. Table A.4 show similar results when we exclude the individual level controls. These results at least suggest that our main result—that mining induces corruption—may apply not only to industrial scale mining, but also to artisanal mining, while we remind that investigating this more thoroughly would require more detailed data on artisanal, or at least diamond, mine openings.

We robustness tested these results using data from the U.S. Geological Survey (USGS). The USGS data covers a wider variety of mines and deposits beyond those of industrial size, but has the drawback of not including time-varying production levels. The results are a bit weaker but still resemble the above findings. While the results point in the right direction when including individual-level controls for police bribes (p=0.12), they are statistically significant at conventional levels when omitting these controls (see Tables A.5 and A.6).

Table A.3: Correlations between diamond mines and corruption.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
At least one diamond mine within 50 km	0.033	0.020	−0.026	0.026
	(2.70)	(1.78)	(−1.61)	(1.79)
Mean dep. var	0.227	0.230	1.309	1.610
R-squared	0.076	0.063	0.094	0.100
No. of observations	96,949	97,057	66,728	87,718

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, and for urban area, age, age^2, female and education. The sample includes round 2, 3, 4 and 5 of the Afrobarometer, as well as round 2.5 for South Africa. Geocodes for all rounds are from our own Google-maps matching algorithm. When missing, the data are complemented with geocodes from Nunn and Wantchekon (2011) and Deconinck and Verpoorten (2013) for round 3 and 4, respectively. Geocoding in South Africa is based on census enumeration areas, as are some observations in Sierra Leone. Data on diamond mines come from Gilmore et.al., (2005).

Table A.4: Correlations between diamond mines and corruption without individual controls.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
At least one diamond mine within 50 km	0.037	0.021	−0.020	0.028
	(2.92)	(1.85)	(−1.24)	(1.87)
Mean dep. var	0.225	0.230	1.307	1.610
R-squared	0.060	0.048	0.087	0.091
No. of observations	100,270	100,402	67,369	90,440

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects. Data on diamond mines come from Gilmore et.al., (2005). See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.5: Correlations between USGS mines and corruption.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
usgs50	0.011	0.0094	0.041	0.046
	(1.55)	(1.47)	(3.57)	(4.80)
Mean dep. var	0.227	0.230	1.309	1.610
R-squared	0.076	0.063	0.095	0.100
No. of observations	96,949	97,057	66,728	87,718

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, and for urban area, age, age^2, female and education. Data on mines come from USGS. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.6: Correlations between USGS mines and corruption without individual controls.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
usgs50	0.036	0.032	0.076	0.086
	(5.11)	(4.88)	(6.55)	(8.65)
Mean dep. var	0.225	0.230	1.307	1.610
R-squared	0.061	0.049	0.089	0.093
No. of observations	100,270	100,402	67,369	90,440

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects. Data on mines come from USGS. See notes to table A.3 for information on Afrobarometer waves and sample construction.

A.2.2 Oil extraction

In terms of total production value, oil extraction is the dominant mode of natural resource extraction, and, unfortunately, the RMD data does not cover oil. Nevertheless, many of the same dynamics that we expect to apply to (non-oil) mineral extraction, should also be expected to operate at least for onshore oil extraction. Indeed, many of the seminal contributions to the "resource curse" literature are developed on the basis of experiences with oil production (see Ross, 2012).

To check whether the pattern discovered for mining also might be there for oil extraction, we use data from PETRODATA (Lujala, Rød and Thieme, 2007) to identify all onshore oil deposits relevant for our sample. This dataset contains GIS-polygons for all oil deposits between 1946 and 2003. Again we create buffer zones for being within 50 kilometers from a deposit. Since the dataset ends in 2003, we have insufficient temporal variation corresponding to our Afrobarometer waves, and thus perform purely cross sectional analyses. To investigate whether the presence of oil deposits is correlated with our corruption indicators, we create binary variables registering whether our respondent clusters are within 50 km from a petroleum deposit polygon (1 =Overlap, 0 =No overlap).

Table A.7 shows the results from this analysis, for all of our corruption measures, with all controls (including country- and year-fixed effects). The table shows that there are positive correlations between the presence of oil deposits and reported and experienced corruption. All coefficients are in the expected direction, and they are significant at 5%, except for the measure that typically yields the strongest results for mines, namely bribes paid to the police.

As the dataset on oil only has observations from further back in time, the argument for excluding individual-level control variables (because of post-treatment effects) is even stronger. When estimating the models without the individual-level controls (Table A.8), there is a significant correlation also with police bribes. While we believe the sum of these results provide some suggestive evidence that the mining–corruption link also applies to oil, we note that we can not conclude with much certainty based on this analysis, particularly since we do not have enough temporal variation to properly identify causal effects.

Table A.7: Correlations between oil presence and corruption.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Onshore oil cluster	0.040	0.053	0.085	0.099
	(1.50)	(2.06)	(3.51)	(3.68)
Mean dep. var	0.227	0.230	1.309	1.610
R-squared	0.076	0.064	0.095	0.100
No. of observations	96,949	97,057	66,728	87,718

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, and for urban area, age, age^2, female and education. Data on onshore oil deposits from PETRODATA. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.8: Correlations between oil presence and corruption. No individual level controls.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Onshore oil cluster	0.057	0.062	0.11	0.12
	(2.22)	(2.44)	(4.27)	(4.24)
Mean dep. var	0.225	0.230	1.307	1.610
R-squared	0.060	0.049	0.088	0.092
No. of observations	100,270	100,402	67,369	90,440

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects. Data on onshore oil deposits from PETRODATA. See notes to table A.3 for information on Afrobarometer waves and sample construction.

In sum, while it is hard to conclude based on the cross-sectional evidence presented in this Appendix section, there *seems* to be a similar pattern when it comes to inducing local corruption for onshore oil extraction *and* for artisanal mining (as proxied by diamond mines).

A.3 Placebo tests on national-level corruption measures

We here report a simple placebo analysis. The placebo tests are conducted by investigating whether local mine openings have effects on corruption perceptions where they shouldn't (as explained in the paper), namely on perceived *national corruption* (which, in brief, should be similar to individuals across the country, in mining and non-mining areas alike). We find no evidence that mine openings affect perceptions of national level corruption. As shown in Table A.9, we employed the two relevant measures from the Afrobarometer, pertaining to perceived corruption with national government officials and the President.

Table A.9: Placebo tests: Mine openings and perceived national corruption.

	Perceptions of Corruption	
	(1) President	(2) National gov.
Active 50 km	0.010	0.043
	(0.70)	(1.05)
Inactive 50 km	0.038	0.052
	(0.98)	(0.93)
Difference in differences	−0.027	−0.009
F-test: active-inactive=0	0.480	0.032
p-value, F-test	0.488	0.859
Mean dep. var	1.180	1.075
R-squared	0.099	0.019
No. of observations	74,730	1,958

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for country- and year-fixed effects, and for urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

A.4 Sensitivity tests

In this section we present tables reporting the wide variety of sensitivity tests mentioned in the paper, probing whether our main result is an artifact of particular specification choices. A quick summary of these tests is that the results identified in our main models, and particularly for the police bribe index, are robust.

First, we present two tables (A.10 and A.11) showing results for alternative indices of local corruption to those reported in tables in the paper. There, we focus on the two bribe measures that are available in all of the Afrobarometer survey waves, namely bribes to the police and bribes for permits. Yet, there are seven other bribe measures that are available in *some* of the surveys. These are bribes for education, border crossing, services, health care, water, as well as bribes to election officials and bribes to tax officials. Out of the seven bribe items tested, six result in a positive difference-in-differences estimate. The only negative estimate pertains to “Bribe for Water”, and it has a very small coefficient (-0.001) and p-value of 0.981. Further, two difference-in-differences results are statistically significant even at the 1 percent level, namely “Bribe for Services” and “Bribe to Tax officials”. The latter is notable, given that we have very few observations for “Bribe to Tax officials”, which is only asked for South Africa in survey Wave 2.5. Moreover, “Bribe for Border crossing” has a p-value of 0.054. The p-values for the three remaining coefficients that point in the expected direction (pertaining to bribes paid to election officials, and bribes paid for education or healthcare) range from 0.11–0.25.

In all, our main bribe results *seem* to generalize fairly well to other measures of bribe-payments, suggesting a comprehensive “local resource curse”, pertaining to various areas of public life/officials, as a product of mining. Still, we highlight that we have not put these measures through the same strenuous robustness tests as our main measures. Hopefully, future data collection in additional Afrobarometer waves will allow for a closer investigation of whether there are similar or differential patterns of mining-induced corruption across different public spheres.

To provide a brief overview of the other robustness tests in this section, it contains the following tables: We first run analyses with standard errors clustered on the closest mine rather than survey clusters (Table A.12). Thereafter we present results when omitting education from the control set – this could be a "bad control", given that mining may affect education and induce post-treatment bias (Table A.13). We further report models excluding both education and living in an urban area as controls (Table A.14), and models without any individual-level controls (Table A.15).

Relating to this, we try to gauge how sensitive our results are to potential unobserved confounders, in line with the reasoning of, e.g., Altonji, Elder and Taber (2005), Oster (2013) and Imbens and Rubin (2015, 479–500). Based on observing how much our estimate changes when moving from a no-controls model to a model with a full set of controls, we can attempt to estimate how much confounding there *would have to be* for our result to disappear. The assumption behind such an estimate is that coefficient movements arising from the inclusion of observables can inform us about further coefficient movement when including unobservables. Furthermore, Oster (2013) proposes to let this reasoning also depend on the difference in R-squared between the models. Table A.16 shows the no-controls model. When comparing the difference in differences estimate in this model (0.068) to the difference in differences estimate in our baseline model (0.074), we find that the change is only 0.006. Furthermore, the R^2 increases substantially when including controls. This indicates that it would take a very large dose of confounding to make our results disappear. In fact, the effect of the unobserved omitted variables would have to be at least *12 times as large* as the effect of the included observable controls. In addition, they would, in this case, have to work "in the opposite direction".

We also experiment with different sizes for the respondent buffers, by investigating whether our results are similar when using a 25km rather than 50km buffer (Table A.17). This is the only type of test where our results are substantially weakened, and there are (as we discuss in the paper) very good reasons for why this is the case. To reiterate, the number of active and inactive observations fall dramatically. The weakening of results could also partly be due to attenuation. Even with our precise geolocation strategy, our validation test on South Africa show that the average location error is 13km, and errors are likely larger for many other countries. Hence, using the 25km threshold could lead to substantial measurement error for both *active* and *inactive*; several individuals living in mining areas are likely measured as living outside them, and *vice versa*.

Thereafter, we report models investigating whether our results are artifacts of the chosen linear specification, by fitting ordinal logit models instead of OLS (Table A.18 and Table A.19), and by testing models run on dummy dependent variables (Table A.20) separating those that have paid a bribe the last year (or those that answer the corruption perception measures in the positive) from all other individuals. Our results are robust in these specifications. Finally, we tested models guarding against the possibility, discussed in the paper, that our active mining areas could be different from our inactive due to reasons corresponding with active mines typically having been located in these areas a longer time ago. More specifically, we restrict the sample to mines opening within ± 10 years from the interview year of the Afrobarometer survey. Again, our main results hold up quite well.

Table A.10: The baseline estimation for other measures of bribe-payments

	Bribes		
	(1) School	(2) Services	(3) Border crossing
Active 50 km	0.0078	−0.0030	0.00097
	(1.19)	(−0.35)	(0.06)
Inactive 50 km	−0.015	−0.060	−0.045
	(−0.84)	(−4.79)	(−1.86)
Difference in differences	0.023	0.057	0.046
F-test: active-inactive=0	1.922	19.990	3.718
p-value, F-test	0.166	0.000	0.054
Mean dep. var	0.144	0.141	0.140
R-squared	0.054	0.062	0.029
No. of observations	67,898	38,938	12,467

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for country- and year-fixed effects, and for urban area, age, age^2, female and education. Column 1 includes Afrobarometer waves 2, 3 and 5. Column 2 includes waves 2 and 3. Column 3 includes wave 2. See notes to table A.3 for information on geocoding.

Table A.11: The baseline estimation for other measures of bribe-payments

	Bribes			
	(1) Healthcare	(2) Election officials	(3) Water	(4) Tax officials
Active 50 km	0.0046	0.014	0.0019	0.078
	(0.40)	(1.13)	(0.21)	(7.26)
Inactive 50 km	−0.032	−0.028	0.0029	0.018
	(−1.02)	(−1.05)	(0.06)	(1.94)
Difference in differences	0.037	0.042	−0.001	0.061
F-test: active-inactive=0	1.313	2.560	0.001	29.094
p-value, F-test	0.252	0.110	0.981	0.000
Mean dep. var	0.256	0.305	0.151	0.053
R-squared	0.094	0.099	0.043	0.040
No. of observations	51,549	53,352	53,670	2,254

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for country- and year-fixed effects, and for urban area, age, age^2, female and education. Columns 1 and 2 includes Afrobarometer waves 3 and 5. Column 3 includes waves 4 and 5, and column 4 includes wave 2.5 from South Africa. See notes to table A.3 for information on geocoding.

Table A.12: The baseline estimation with standard errors clustered at closest mine.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.024	0.015	0.026	0.069
	(1.970)	(1.514)	(1.223)	(4.254)
Inactive 50 km	−0.050	−0.024	−0.089	0.063
	(−3.032)	(−1.113)	(−1.484)	(1.789)
Difference in differences	0.074	0.039	0.115	0.006
F-test: active-inactive=0	23.290	3.485	3.600	0.031
p-value, F-test	0.000	0.063	0.059	0.860
Mean dep. var	0.225	0.229	1.307	1.609
R-squared	0.077	0.064	0.096	0.101
No. of observations	92,762	92,863	63,481	83,860

Notes: Standard errors are clustered at closest mine and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for country- and year-fixed effects, and for urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.13: Effects of mine openings on corruption in the 33 country sample. Robustness testing when excluding education as control.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.025	0.017	0.028	0.071
	(3.202)	(2.372)	(1.942)	(5.326)
Inactive 50 km	−0.050	−0.024	−0.087	0.064
	(−3.766)	(−1.051)	(−1.700)	(1.924)
Difference in differences	0.075	0.041	0.115	0.007
F-test: active-inactive=0	29.484	3.223	4.851	0.049
p-value, F-test	0.000	0.073	0.028	0.824
Mean dep. var	0.225	0.229	1.307	1.609
R-squared	0.074	0.060	0.094	0.099
No. of observations	92,945	93,047	63,610	84,014

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for country- and year-fixed effects, and for urban area, age, age^2 and female. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.14: Effects of mine openings on corruption in the 33 country sample. Robustness testing when excluding education and urban as controls.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.036	0.024	0.045	0.088
	(4.539)	(3.223)	(3.103)	(6.570)
Inactive 50 km	−0.043	−0.021	−0.080	0.065
	(−3.259)	(−0.952)	(−1.544)	(1.962)
Difference in differences	0.079	0.045	0.125	0.023
F-test: active-inactive=0	32.311	4.019	5.609	0.479
p-value, F-test	0.000	0.045	0.018	0.489
Mean dep. var	0.224	0.230	1.307	1.611
R-squared	0.071	0.057	0.090	0.095
No. of observations	94,755	94,876	63,610	85,621

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for country- and year-fixed effects, and for age, age^2 and female. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.15: Effects of mine openings on corruption in the 33 country sample. Robustness testing when excluding all individual level controls.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.038	0.027	0.048	0.092
	(4.769)	(3.555)	(3.326)	(6.851)
Inactive 50 km	−0.038	−0.016	−0.075	0.069
	(−2.684)	(−0.706)	(−1.445)	(2.122)
Difference in differences	0.076	0.043	0.123	0.023
F-test: active-inactive=0	27.060	3.406	5.480	0.474
p-value, F-test	0.000	0.065	0.019	0.491
Mean dep. var	0.223	0.229	1.305	1.609
R-squared	0.062	0.049	0.088	0.092
No. of observations	96,028	96,153	64,097	86,536

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for country- and year-fixed effects. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.16: Effects of mine openings on corruption without control variables.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	−0.056	−0.060	0.019	−0.084
	(−4.970)	(−6.872)	(0.854)	(−4.932)
Inactive 50 km	−0.124	−0.110	−0.085	−0.118
	(−5.076)	(−2.741)	(−1.222)	(−4.026)
Difference in differences	0.068	0.049	0.104	0.033
F-test: active-inactive=0	7.337	1.506	2.086	1.138
p-value, F-test	0.007	0.220	0.149	0.286
Mean dep. var	0.223	0.229	1.305	1.609
R-squared	0.001	0.002	0.000	0.001
No. of observations	96,028	96,153	64,097	86,536

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions are without any control variables. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.17: Effects of mine openings on corruption in the 33 country sample. Robustness testing with 25 kilometer buffer zones.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
active25	0.003	−0.002	0.019	0.041
	(0.304)	(−0.245)	(1.085)	(2.798)
inactive25	−0.023	0.013	−0.206	0.013
	(−1.120)	(0.355)	(−2.475)	(0.275)
Difference in differences	0.025	−0.015	0.225	0.028
F-test: active-inactive=0	1.426	0.156	7.063	0.333
p-value, F-test	0.232	0.692	0.008	0.564
Mean dep. var	0.227	0.231	1.308	1.609
R-squared	0.077	0.064	0.096	0.101
No. of observations	95,028	95,138	65,260	85,922

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for country- and year-fixed effects, and for urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.18: 50 kilometer buffer zones, ordered logit.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
main				
Active 50 km	0.221	0.147	0.059	0.151
	(4.591)	(3.477)	(1.734)	(5.252)
Inactive 50 km	−0.303	−0.177	−0.265	0.140
	(−2.057)	(−1.018)	(−2.011)	(1.952)
Pseudo R-squared	0.081	0.066	0.043	0.048
No. of observations	92,762	92,863	63,481	83,860

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests not presented because they have no straightforward interpretation in an ordered logit regression. All regressions control for country- and year-fixed effects, and for urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.19: 25 kilometer buffer zones, ordered logit.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
main				
Active 25 km	0.124	0.076	0.045	0.088
	(2.208)	(1.517)	(1.043)	(2.821)
Inactive 25 km	−0.124	0.007	−0.541	0.052
	(−0.808)	(0.034)	(−2.374)	(0.478)
Pseudo R-squared	0.081	0.066	0.043	0.048
No. of observations	95,028	95,138	65,260	85,922

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests not presented because they have no straightforward interpretation in an ordered logit regression. All regressions control for country- and year-fixed effects, and for urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.20: Effects of mine openings on corruption using dummies. 50 kilometer buffer zones.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.017	0.012	−0.009	0.005
	(4.122)	(2.897)	(−1.424)	(1.298)
Inactive 50 km	−0.023	−0.017	−0.046	0.013
	(−2.420)	(−1.460)	(−1.803)	(0.918)
Difference in differences	0.039	0.029	0.037	−0.008
F-test: active-inactive=0	17.180	6.001	1.987	0.307
p-value, F-test	0.000	0.014	0.159	0.580
Mean dep. var	0.127	0.145	0.849	0.908
R-squared	0.081	0.070	0.089	0.024
No. of observations	92,762	92,863	63,481	83,860

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. Dependent variable is a dummy taking the value 1 if respondent answers positively on the bribery/corruption question, and 0 otherwise. All regressions control for country- and year-fixed effects, and for urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.21: Effects of mine openings on corruption: first mine opens +/− 10 years from interview year. 50 kilometer buffer zones.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.023	0.016	0.020	0.051
	(1.875)	(1.259)	(0.620)	(2.221)
Inactive 50 km	−0.037	−0.015	−0.080	0.075
	(−2.755)	(−0.654)	(−1.531)	(2.208)
Difference in differences	0.059	0.031	0.100	−0.025
F-test: active-inactive=0	11.864	1.324	2.804	0.410
p-value, F-test	0.001	0.250	0.094	0.522
Mean dep. var	0.229	0.234	1.300	1.614
R-squared	0.079	0.066	0.099	0.106
No. of observations	81,750	81,857	56,351	73,586

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. Sample restricted to observations where the first active mine within 50 km opened within a range of −10 to 10 years from interview year. All regressions control for country- and year-fixed effects, and for urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

A.5 Alternative unit of analysis

In our main analyses, the units of study are individuals nested in survey clusters and 50km buffers. While we do test models clustering standard errors on both survey clusters and mines, one could argue that the "real" unit of analysis is, in fact, the survey cluster and not the individual, since there is no spatial variation in the location of individuals within each cluster. To make sure that our results do not depend on our choice of unit of analysis, we robustness test models where the units are survey clusters, i.e. the responses are collapsed to the survey cluster by taking the mean of all variables. We find that our results are actually strengthened when implementing this change, as can be seen in table A.22.

Table A.22: Effects of mine openings on corruption at the cluster level.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.048	0.029	0.072	0.097
	(5.726)	(3.628)	(4.105)	(6.772)
Inactive 50 km	−0.048	−0.035	−0.001	0.086
	(−3.504)	(−2.574)	(−0.014)	(2.356)
Difference in differences	0.095	0.064	0.073	0.011
F-test: active-inactive=0	43.510	20.350	1.297	0.099
p-value, F-test	0.000	0.000	0.255	0.753
Mean dep. var	0.214	0.206	1.342	1.588
R-squared	0.243	0.227	0.261	0.283
No. of observations	8,195	8,196	6,324	8,167

Notes: Standard errors are robust to heteroskedasticity and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. Unit of analysis is the survey cluster/Enumeration Area, and all measures are aggregated by taking the mean. All regressions control for country- and year-fixed effects, and for urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

A.6 Production levels and number of active mines

While the RMD data contain fairly large-scale industrial mines, there are still differences in production volumes and values across the mines in our dataset. Thus, we further investigate whether our treatment effect depends on the "dosage" (i.e., the level of exposure to treatment). For example, one could suspect that larger mines (i.e., with higher production levels) might generate more corruption than smaller ones. One reason is that it increases the probability that a random individual risks being exposed to corruption generated by the nearby mine, or is related to the mine in some way, either through direct labor or indirect linkages. To investigate this, we estimate separate models for high- and low-dosage mines, where the high-low cutoff is set at the median production volume (in terms of extracted mass). For perceptions we see that the difference-in-differences estimate is never statistically significant. Considering the two bribe variables, the difference-in-differences estimates suggest that the effects are larger for low-production mines than for high-production ones. This is partly due to the fact that our estimates for *inactive* are more strongly negative for low-production mines. This might result from a stronger selection-into-mine-placement effect for low-production mines, which would make sense if companies were less concerned about corruption for high-production enterprises. When we use production value instead of extracted mass we get very similar results. In spite of these differences, the key finding is that for our police bribe measure, we find a clear effect on corruption, both for high-production/high-value and for low-production/low-value mines.

We also test whether the effects of mining on corruption are seemingly increasing in the number of mines present in an area, or whether the main difference is simply due to being/not being an active mining area. Tables A.27 (linear number mines) and A.28 (log number mines) report results from regressions on the active dummy as well as the (linear/log) number of active mines within 50 km. For the first two columns of both tables

Table A.23: Split sample: Above median production.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.034	0.016	0.026	0.067
	(3.103)	(1.604)	(1.446)	(3.783)
Inactive 50 km	−0.035	−0.001	−0.091	0.041
	(−2.459)	(−0.039)	(−1.178)	(1.072)
Difference in differences	0.070	0.017	0.117	0.026
F-test: active-inactive=0	17.075	0.332	2.219	0.446
p-value, F-test	0.000	0.564	0.136	0.504
Mean dep. var	0.230	0.235	1.305	1.614
R-squared	0.079	0.065	0.097	0.106
No. of observations	84,246	84,352	58,231	75,899

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. All regressions control for country- and year-fixed effects. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.24: Split sample: Below median production.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.030	0.022	0.033	0.090
	(2.573)	(2.204)	(1.564)	(5.083)
Inactive 50 km	−0.059	−0.065	−0.054	0.181
	(−2.038)	(−2.110)	(−0.774)	(2.722)
Difference in differences	0.089	0.087	0.086	−0.091
F-test: active-inactive=0	8.259	7.153	1.455	1.786
p-value, F-test	0.004	0.008	0.228	0.181
Mean dep. var	0.233	0.235	1.308	1.623
R-squared	0.077	0.065	0.097	0.103
No. of observations	83,520	83,615	58,142	75,458

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. All regressions control for country- and year-fixed effects. See notes to table A.3 for information on Afrobarometer waves and sample construction.

(the bribe payment measures), the coefficients on (log) number of active mines are negative, but statistically insignificant at 5%. In other words, conditional on being an active mining area, there is no clear evidence that the number of mines affects bribes. For the corruption perception measures, however, the coefficients on number of active mines are positive,

Table A.25: Split sample: Above median production value.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.031	0.011	0.025	0.050
	(2.588)	(1.061)	(1.317)	(2.758)
Inactive 50 km	−0.033	−0.002	−0.089	0.034
	(−2.096)	(−0.089)	(−1.299)	(0.975)
Difference in differences	0.064	0.013	0.115	0.016
F-test: active-inactive=0	12.347	0.204	2.625	0.192
p-value, F-test	0.000	0.651	0.105	0.662
Mean dep. var	0.230	0.234	1.305	1.614
R-squared	0.078	0.064	0.097	0.105
No. of observations	83,844	83,950	57,909	75,612

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. All regressions control for country- and year-fixed effects. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.26: Split sample: Below median production value.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.029	0.022	0.035	0.097
	(2.500)	(2.209)	(1.602)	(5.267)
Inactive 50 km	−0.097	−0.086	−0.012	0.265
	(−3.824)	(−2.207)	(−0.111)	(2.440)
Difference in differences	0.125	0.108	0.047	−0.169
F-test: active-inactive=0	21.499	7.413	0.191	2.356
p-value, F-test	0.000	0.006	0.662	0.125
Mean dep. var	0.233	0.236	1.308	1.623
R-squared	0.078	0.065	0.097	0.104
No. of observations	82,976	83,072	57,809	74,965

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. All regressions control for country- and year-fixed effects. See table A.9 for information on Afrobarometer waves and sample construction. See notes to table A.3 for information on Afrobarometer waves and sample construction.

and highly significant. The estimated effects are, however, not very large substantially; for perceived corruption among local councilors, an extra mine in an already active area leads to a $\frac{0.012}{1.307} = 0.9\%$ increase from the average corruption level, according to the estimate in Table A.27. To gauge the size of this effect from a quick calculation, Table A.29 reports a

Table A.27: Number of mines conditional on being an active mining area

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.028	0.020	−0.003	0.045
	(3.087)	(2.401)	(−0.189)	(3.003)
Number of active 50 km	−0.001	−0.002	0.012	0.008
	(−0.468)	(−1.277)	(4.261)	(3.400)
Mean dep. var	0.225	0.229	1.307	1.609
R-squared	0.077	0.064	0.096	0.101
No. of observations	92,762	92,863	63,481	83,860

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female, and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.28: Log number of mines conditional on being an active mining area

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.038	0.046	−0.084	−0.006
	(2.229)	(2.563)	(−2.410)	(−0.164)
Log number of active 50 km	−0.002	−0.006	0.024	0.015
	(−0.767)	(−1.913)	(3.540)	(2.403)
Mean dep. var	0.225	0.229	1.307	1.609
R-squared	0.077	0.064	0.096	0.101
No. of observations	92,762	92,863	63,481	83,860

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female, and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

regression where we compare corruption in active areas with *only one single mine* to inactive areas. Moving from no active to one active mine gives an estimated increase in perceived corruption of local councilors of 0.084. This quick exercise suggests that it would require about seven additional active mines to achieve an effect of the same size as moving from being an inactive mining area to a single active mine.[2]

[2]We recommend not to take these calculations at face value, however, for instance because predictions in OLS estimation with ordered variables is likely to not give correct estimates.

Another, and in our view less problematic, way to investigate treatment intensity is to probe whether the difference-in-differences estimates get stronger as the number of active mines (in the area) increases, and we compare these resulting coefficients to the coefficient for being inactive mining area. Since it is not straightforward to investigate this in a parametric way (because of the difference-in-differences comparisons), we proceed by comparing ≥ 2 active mines to *inactive*, then ≥ 3 to *inactive*, and so on, increasing the (minimum required) number of active mines in each test by one. Tables A.30 though A.33 perform these comparisons, varying the number of mines from ≥ 2 to ≥ 5 (we have tested up to 10 mines, and the results follow the same pattern when further adding mines; we therefore report the four first tables for brevity). This essentially constitutes a non-parametric test of whether our treatment effect varies with intensity, captured by the number of mines. Tables A.30 to A.33 show that the difference-in-differences estimates typically become somewhat stronger as the number of mines in the active category increases, although the decidedly most important increase occurs when going from a non-mining to a mining area (with the exception of perceived police corruption, for which having three or more mines gives a strong boost). Thus, for most of the analyses, the difference-in-differences coefficients turn stronger with each additional mine, and the F-tests increase accordingly. This indicates that the extent of corruption in a survey area grows with the number of mines, although we again note that the largest difference in terms of increased corruption happens when the first mine is opened.

Table A.29: One single active mine within 50 km vs inactive.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
One Active 50 km	0.032	0.020	0.009	0.064
	(2.972)	(2.105)	(0.485)	(3.880)
Inactive 50 km	−0.047	−0.022	−0.075	0.075
	(−3.467)	(−0.977)	(−1.434)	(2.220)
Difference in differences	0.079	0.042	0.084	−0.011
F-test: active-inactive=0	23.325	2.892	2.332	0.085
p-value, F-test	0.000	0.089	0.127	0.771
Mean dep. var	0.229	0.235	1.297	1.610
R-squared	0.079	0.065	0.097	0.105
No. of observations	86,983	87,082	59,811	78,305

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female, and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.30: At least two active mines vs inactive.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
$\geq$2 Active 50 km	0.021	0.003	0.078	0.088
	(1.881)	(0.373)	(3.610)	(4.784)
Inactive 50 km	−0.043	−0.020	−0.081	0.064
	(−3.222)	(−0.893)	(−1.558)	(1.905)
Difference in differences	0.063	0.023	0.158	0.024
F-test: active-inactive=0	17.098	1.165	8.453	0.465
p-value, F-test	0.000	0.281	0.004	0.495
Mean dep. var	0.229	0.232	1.314	1.621
R-squared	0.078	0.066	0.097	0.103
No. of observations	84,022	84,123	58,078	76,007

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female, and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.31: At least three active mines vs inactive.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
≥3 Active 50 km	0.034	0.012	0.098	0.132
	(2.810)	(1.150)	(4.042)	(6.706)
Inactive 50 km	−0.039	−0.018	−0.080	0.071
	(−2.970)	(−0.808)	(−1.542)	(2.109)
Difference in differences	0.073	0.030	0.178	0.061
F-test: active-inactive=0	21.415	1.852	10.316	2.908
p-value, F-test	0.000	0.174	0.001	0.088
Mean dep. var	0.230	0.233	1.314	1.622
R-squared	0.078	0.065	0.099	0.104
No. of observations	82,549	82,654	57,055	74,623

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female, and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.32: At least four active mines vs inactive.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
≥4 Active 50 km	0.033	0.012	0.113	0.149
	(2.832)	(1.076)	(4.237)	(6.959)
Inactive 50 km	−0.039	−0.017	−0.077	0.075
	(−2.899)	(−0.755)	(−1.480)	(2.201)
Difference in differences	0.072	0.029	0.190	0.074
F-test: active-inactive=0	20.259	1.698	11.387	4.084
p-value, F-test	0.000	0.193	0.001	0.043
Mean dep. var	0.231	0.233	1.314	1.622
R-squared	0.078	0.065	0.099	0.104
No. of observations	81,780	81,887	56,608	73,899

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female, and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.33: At least five active mines vs inactive.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
≥5 Active 50 km	0.039	0.020	0.124	0.152
	(2.982)	(1.614)	(4.040)	(6.566)
Inactive 50 km	−0.037	−0.017	−0.074	0.078
	(−2.815)	(−0.745)	(−1.410)	(2.297)
Difference in differences	0.076	0.037	0.198	0.074
F-test: active-inactive=0	20.251	2.650	11.538	3.848
p-value, F-test	0.000	0.104	0.001	0.050
Mean dep. var	0.231	0.234	1.313	1.622
R-squared	0.079	0.066	0.099	0.105
No. of observations	81,069	81,175	56,140	73,213

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female, and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

A.7 Sub-sample analysis: South Africa

This section presents a separate study based only on South African data, employing Afrobarometer Waves 2, 2.5, 3, 4 and 5. South Africa is among the world's leading producers of several minerals, including gold and diamonds; a closer study of South Africa is thus interesting in itself. Furthermore, the matching of individuals to mines using geographical coordinates can be done very precisely for South Africa. As noted, this is due to the fact that we have the "true" enumeration areas for South Africa. While only covering one country—but numerous respondents (more than $\frac{1}{10}$ of the 33 country sample) and mines (about $\frac{3}{5}$ of the total)—the estimates for South Africa *could* thus be more precise due to smaller measurement errors stemming from inaccurate matching of mines and respondents.

Table A.34: Descriptive statistics calculated for the 33-country sample of Model 1, Table 1, and for the South Africa sample

	Total sample		South Africa	
	Mean	SD	Mean	SD
Mining variables				
Kilometers	207.888	(202.537)	85.903	(93.248)
Active 50 km	0.157	(0.363)	0.516	(0.500)
Inactive 50 km	0.014	(0.117)	0.067	(0.251)
Active 25 km	0.080	(0.271)	0.316	(0.465)
Inactive 25 km	0.007	(0.083)	0.026	(0.160)
Dependent variables: Paid a bribe last year				
– to the Police	0.225	(0.657)	0.108	(0.430)
– for a Permit	0.227	(0.624)	0.093	(0.384)
Perception of corruption				
Local councilors	1.306	(0.847)	1.495	(0.853)
Police	1.607	(0.890)	1.469	(0.795)
Control variables				
Urban	0.427	(0.495)	0.659	(0.474)
Age	36.658	(14.622)	38.911	(15.460)
Female	0.498	(0.500)	0.500	(0.500)
Education	3.278	(2.019)	4.150	(1.680)
N	92762		10566	

Another benefit of looking at South Africa is the fact that it contains much variation in both mining activity and survey locations. In the sample used for the baseline models in the main text (Table 1), the average distance from a respondent to a mine is 208km (see Table A.34). Approximately 15.7% of respondents live within 50km of an active mine, while 1.4% live within 50km of an inactive mine (but no active mines). For the sample that is restricted to South Africa, the average distance from a respondent to a mine is 86km, while as much as 51.6% of respondents have a mine in their 50km buffer, and 6.7% of respondents have inactive (but no active) mines in their buffer. In short, South Africa have a much higher share of respondents living in mining areas than in the (33-country) baseline sample. Furthermore, as many as 301 mines out of 496 (in the total sample) are located in South Africa. Hence, South Africa contains much information, in terms of both mining and respondent data.

In Table A.35 we report estimated effects of mine openings on corruption in South Africa, using our baseline specifications. When considering our favored dependent variables—those measuring reported bribes paid—the results for this sub-sample replicates that of the Africa-wide sample.[3] First, also these regressions find that active mining areas are positively correlated with paying bribes, both to the police and for obtaining permits. Second, and more importantly, South Africans systematically report paying more bribes once a mine opens within 50km. The difference between *active* and *inactive* is significant at all conventional levels. The point estimates are substantial; opening a mine increases the bribe-item scores with 0.10 (police) and 0.05 (permit). In comparison, the *average scores* on these measures for the South African sample are 0.11 and 0.10, respectively.

As for the 33 country sample, the results are somewhat weaker for the corruption perception measures. While *active* is statistically significant for both the perception measures as well, our preferred difference-in-differences estimators have the anticipated signs but are statistically insignificant at 5% (although p=0.079 for local councilor corruption perceptions).

[3]Although the results are somewhat weaker, the same patterns emerge also when analyzing the Africa-wide sample, but excluding South Africa (see the next section of the Appendix).

Table A.35: Effects of mine openings on corruption in South Africa.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.087	0.054	0.125	0.135
	(9.007)	(6.135)	(4.629)	(7.057)
Inactive 50 km	−0.009	0.001	−0.024	0.110
	(−0.641)	(0.056)	(−0.276)	(2.750)
Difference in differences	0.096	0.053	0.149	0.025
F-test: active-inactive=0	38.378	13.116	3.082	0.429
p-value, F-test	0.000	0.000	0.079	0.512
Mean dep. var	0.108	0.096	1.494	1.469
R-squared	0.019	0.009	0.021	0.025
No. of observations	10,566	10,574	5,818	10,020

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for year-fixed effects, urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Nevertheless, we ran a battery of robustness tests also for the South African sample, and report tables with these results in the tail of this Appendix section. Also here, the results hold up, for instance, when adjusting the set of control variables or when using different estimation techniques.

Table A.36 presents the results from mine-fixed effects models. Also here, we find that the result is robust ($t = 4.3$) when bribe payments to the police is the dependent variable. While the estimated effects are in the expected direction also for the other measures, they are insignificant at conventional levels. However, we again note that this is a very conservative estimation strategy, where we only draw on limited data, and it is difficult to identify an effect even if mining activities were to increase corruption. Bearing this caveat in mind, the South Africa results corroborate those from the 33 country sample. Mining activities seemingly increase local corruption, at least when employing measures of corruption not based on perceptions but rather on reporting of actually paid bribes. The finding is particularly clear for bribes paid to the police. The following tables present additional robustness tests on the

Table A.36: Effects of mine openings on corruption in South Africa. Mine-fixed effects

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.127	0.023	0.013	0.016
	(4.341)	(0.836)	(0.163)	(0.379)
Mean dep. var	0.138	0.115	1.545	1.523
R-squared	0.011	0.004	0.016	0.024
No. of observations	6,160	6,167	3,286	5,919

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for mine- and year-fixed effects, urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

South Africa sub-sample.

Table A.37: The baseline estimation in South Africa with standard errors clustered at closest mine.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.087	0.054	0.125	0.135
	(6.110)	(4.120)	(3.333)	(5.583)
Inactive 50 km	−0.009	0.001	−0.024	0.110
	(−0.863)	(0.091)	(−0.347)	(2.777)
Difference in differences	0.096	0.053	0.149	0.025
F-test: active-inactive=0	46.901	13.805	5.332	0.587
p-value, F-test	0.000	0.000	0.022	0.444
Mean dep. var	0.108	0.096	1.494	1.469
R-squared	0.019	0.009	0.021	0.025
No. of observations	10,566	10,574	5,818	10,020

Notes: Standard errors are clustered at closest mine and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for year-fixed effects, and for urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.38: Effects of mine openings on corruption South Africa. Robustness testing when excluding education as control.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.088	0.055	0.124	0.136
	(9.075)	(6.200)	(4.596)	(7.122)
Inactive 50 km	−0.009	0.000	−0.019	0.110
	(−0.661)	(0.034)	(−0.227)	(2.761)
Difference in differences	0.097	0.054	0.144	0.026
F-test: active-inactive=0	39.342	13.560	2.870	0.462
p-value, F-test	0.000	0.000	0.090	0.497
Mean dep. var	0.108	0.096	1.494	1.469
R-squared	0.018	0.009	0.020	0.025
No. of observations	10,580	10,588	5,823	10,029

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for year-fixed effects, and for urban area, age, age^2, and female. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.39: Effects of mine openings on corruption in South Africa. Robustness testing when excluding education and urban as controls.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.084	0.051	0.129	0.146
	(8.619)	(5.692)	(4.776)	(7.600)
Inactive 50 km	−0.020	−0.009	−0.007	0.135
	(−1.387)	(−0.630)	(−0.087)	(3.377)
Difference in differences	0.103	0.060	0.136	0.011
F-test: active-inactive=0	44.955	16.675	2.561	0.080
p-value, F-test	0.000	0.000	0.110	0.777
Mean dep. var	0.108	0.096	1.494	1.469
R-squared	0.017	0.007	0.020	0.023
No. of observations	10,580	10,588	5,823	10,029

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for year-fixed effects, and for age, age^2 and female. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.40: Effects of mine openings on corruption in South Africa. Robustness testing when excluding all individual level controls.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.085	0.052	0.134	0.151
	(8.620)	(5.805)	(4.999)	(7.910)
Inactive 50 km	−0.018	−0.008	0.003	0.139
	(−1.284)	(−0.596)	(0.029)	(3.472)
Difference in differences	0.104	0.060	0.132	0.013
F-test: active-inactive=0	43.875	17.049	2.387	0.105
p-value, F-test	0.000	0.000	0.123	0.746
Mean dep. var	0.109	0.096	1.494	1.470
R-squared	0.014	0.006	0.018	0.020
No. of observations	10,710	10,719	5,880	10,143

Notes: South Africa sample. Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for year-fixed effects. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.41: Effects of mine openings on corruption in South Africa. Robustness testing with 25 kilometer buffer zones.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 25 km	0.063	0.041	0.091	0.062
	(5.592)	(3.994)	(3.204)	(3.121)
Inactive 25 km	0.022	0.025	0.006	0.160
	(0.723)	(0.800)	(0.051)	(2.653)
Difference in differences	0.041	0.016	0.086	−0.098
F-test: active-inactive=0	1.664	0.244	0.568	2.533
p-value, F-test	0.197	0.621	0.451	0.112
Mean dep. var	0.109	0.100	1.507	1.475
R-squared	0.012	0.006	0.018	0.021
No. of observations	10,914	10,925	6,109	10,366

Notes: South Africa sample. Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for year-fixed effects, urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.42: 50 kilometer buffer zones, ordered logit.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
main				
Active 50 km	0.938	0.658	0.287	0.336
	(9.391)	(6.821)	(4.808)	(7.269)
Inactive 50 km	−0.098	0.133	−0.075	0.246
	(−0.407)	(0.687)	(−0.396)	(2.567)
Pseudo R-squared	0.034	0.022	0.009	0.011
No. of observations	10,566	10,574	5,818	10,020

Notes: South Africa sample. Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests not presented because they have no straightforward interpretation in an ordered logit regression. All regressions control for year-fixed effects, urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.43: 25 kilometer buffer zones, ordered logit.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
main				
Active 25 km	0.661	0.443	0.213	0.156
	(7.471)	(4.878)	(3.434)	(3.277)
Inactive 25 km	−0.031	0.136	0.021	0.414
	(−0.106)	(0.494)	(0.086)	(2.816)
Pseudo R-squared	0.024	0.017	0.007	0.009
No. of observations	10,914	10,925	6,109	10,366

Notes: South Africa sample. Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests not presented because they have no straightforward interpretation in an ordered logit regression. All regressions control for year-fixed effects, urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.44: Effects of mine openings on corruption using dummies. 50 kilometer buffer zones.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.060	0.041	0.008	0.011
	(10.209)	(7.173)	(0.830)	(1.764)
Inactive 50 km	−0.004	0.006	−0.008	0.022
	(−0.465)	(0.575)	(−0.262)	(1.824)
Difference in differences	0.064	0.035	0.016	−0.011
F-test: active-inactive=0	39.920	11.257	0.268	0.855
p-value, F-test	0.000	0.001	0.605	0.355
Mean dep. var	0.073	0.069	0.896	0.915
R-squared	0.022	0.014	0.021	0.021
No. of observations	10,566	10,574	5,818	10,020

Notes: South Africa sample. Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. Dependent variable is a dummy taking the value 1 if respondent answers positively on the bribery/corruption question, and 0 otherwise. All regressions control for year-fixed effects, urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.45: Effects of mine openings on corruption: first mine opens +/– 10 years from interview year. 50 kilometer buffer zones.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.061	0.040	0.120	0.079
	(3.692)	(2.794)	(2.477)	(2.298)
Inactive 50 km	0.001	0.012	−0.016	0.097
	(0.042)	(0.848)	(−0.186)	(2.345)
Difference in differences	0.061	0.028	0.137	−0.018
F-test: active-inactive=0	8.686	2.399	2.074	0.137
p-value, F-test	0.003	0.122	0.150	0.712
Mean dep. var	0.075	0.076	1.440	1.413
R-squared	0.010	0.009	0.017	0.019
No. of observations	6,187	6,189	3,276	5,755

Notes: South Africa sample. Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. Sample restricted to observations where the first active mine within 50 km opened within a range of –10 to 10 years from interview year. All regressions control for year-fixed effects, urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

A.8 Effect heterogeneity; testing across different sub-samples

In the following tables we test for differences in the effects of mining in different types of countries. First, we report results for our baseline models run on the 32 country sample excluding South Africa (Table A.46). South Africa makes up a substantial part of our overall sample in terms of individuals, but particularly in terms of number of mines, as described in the foregoing Appendix section. The results are qualitatively similar when excluding South Africa, but they are weakened. The police bribe index and local councilor corruption perception index remain weakly significant ($p < 0.10$) in this sub-sample.

We also tested across split samples according to theoretically more interesting criteria, investigating whether or not the identified effect is fairly stable (or seemingly different) in relatively rich vs poor, relatively democratic vs autocratic, and relatively corrupt vs less corrupt countries. Country-level data for these variables are drawn from the Quality of Government (QoG) database (Teorell et.al., 2015). When creating sub-samples, we split the sample by the median for the given variable to maximize test power. The first two tables (Tables A.47 and A.48) show the results in relatively rich and relatively poor countries (based on being above or below the median of PPP-adjusted GDP per capita, from the World Development Indicators), and there seems to be a more prominent effect of mine openings on corruption in the richer sub-sample of countries. However, the effect of mine openings on the police bribe index remains statistically significant at the 5% level also for the poor-country sample. The next two tables (Tables A.49 and A.50) show the results in relatively corrupt and less corrupt countries (based on being above or below the median of Control of Corruption index from the World Bank Governance Indicators), and the observed effect of mine openings is fairly similar in the two sets of countries, albeit somewhat stronger for the less corrupt countries. With respect to relatively democratic and non-democratic countries (based on being above or below the median of the Polity index), the estimated

Table A.46: Effects of mine openings on corruption in the 32 country sample, excluding South Africa.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.002	0.002	−0.001	0.042
	(0.224)	(0.268)	(−0.067)	(2.486)
Inactive 50 km	−0.037	−0.011	−0.116	0.066
	(−1.709)	(−0.259)	(−1.846)	(1.192)
Difference in differences	0.039	0.014	0.115	−0.023
F-test: active-inactive=0	2.828	0.092	3.164	0.167
p-value, F-test	0.093	0.761	0.075	0.683
Mean dep. var	0.240	0.246	1.288	1.628
R-squared	0.078	0.063	0.100	0.106
No. of observations	82,196	82,289	57,663	73,840

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for country- and year-fixed effects, and for urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

effect on police bribes is larger for the more democratic countries (while the opposite is the case for perceived local councilor corruption; see Tables A.51 and A.52).

In sum, while there are some indications that mine openings produce worse outcomes in terms of local corruption in national-level contexts associated with "better" political-institutional (democratic regimes and less corrupt countries) and economic (higher national income levels) features, our results are quite stable across sub-samples.

Table A.47: Effects of mine openings in relatively rich countries.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.026	0.020	0.064	0.108
	(3.262)	(2.675)	(3.821)	(7.341)
Inactive 50 km	−0.062	−0.047	−0.032	0.079
	(−4.081)	(−3.168)	(−0.474)	(2.250)
Difference in differences	0.087	0.067	0.097	0.029
F-test: active-inactive=0	32.574	20.863	1.953	0.664
p-value, F-test	0.000	0.000	0.162	0.415
Mean dep. var	0.211	0.204	1.375	1.623
R-squared	0.090	0.075	0.109	0.146
No. of observations	43,679	43,692	29,587	39,875

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. Income is measured using PPP adjusted GDP per capita, from the WDI. Rich countries are measured as above median-income. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.48: Effects of mine openings in relatively poor countries.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.048	0.029	−0.061	0.009
	(2.604)	(1.726)	(−2.222)	(0.328)
Inactive 50 km	−0.025	0.023	−0.130	0.072
	(−1.013)	(0.418)	(−1.757)	(1.035)
Difference in differences	0.073	0.006	0.069	−0.063
F-test: active-inactive=0	6.018	0.009	0.765	0.720
p-value, F-test	0.014	0.923	0.382	0.396
Mean dep. var	0.228	0.236	1.244	1.639
R-squared	0.062	0.051	0.085	0.063
No. of observations	41,004	41,079	27,666	36,739

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. Income is measured using PPP adjusted GDP per capita, from the WDI. Poor countries are operationalized as below-median income. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.49: Effects of mine openings in relatively corrupt countries.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.032	0.025	0.044	0.103
	(4.665)	(3.558)	(2.514)	(6.617)
Inactive 50 km	−0.051	−0.019	−0.050	0.106
	(−3.339)	(−0.775)	(−0.799)	(2.782)
Difference in differences	0.083	0.044	0.094	−0.004
F-test: active-inactive=0	28.867	3.521	2.233	0.008
p-value, F-test	0.000	0.061	0.135	0.927
Mean dep. var	0.115	0.133	1.172	1.430
R-squared	0.032	0.034	0.078	0.040
No. of observations	43,024	43,075	26,844	37,879

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. Relatively corrupt countries are measured as being below the median of Control of Corruption index from the World Bank Governance Indicators. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.50: Effects of mine openings in relatively less corrupt countries.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.036	0.019	−0.030	0.003
	(1.602)	(0.911)	(−0.979)	(0.095)
Inactive 50 km	−0.047	−0.069	−0.183	−0.073
	(−1.367)	(−2.144)	(−3.093)	(−0.794)
Difference in differences	0.083	0.088	0.153	0.076
F-test: active-inactive=0	4.410	5.593	5.167	0.639
p-value, F-test	0.036	0.018	0.023	0.424
Mean dep. var	0.326	0.309	1.434	1.827
R-squared	0.061	0.050	0.080	0.080
No. of observations	41,659	41,696	30,409	38,735

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. Relatively uncorrupt countries are measured as being above the median of Control of Corruption index from the World Bank Governance Indicators. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.51: Effects of mine openings in relatively democratic countries.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.035	0.024	0.043	0.097
	(4.800)	(3.379)	(2.593)	(6.356)
Inactive 50 km	−0.059	−0.042	−0.040	0.059
	(−4.675)	(−3.241)	(−0.688)	(1.654)
Difference in differences	0.094	0.066	0.084	0.038
F-test: active-inactive=0	51.824	24.723	1.951	1.120
p-value, F-test	0.000	0.000	0.163	0.290
Mean dep. var	0.158	0.179	1.260	1.513
R-squared	0.088	0.074	0.089	0.090
No. of observations	51,981	52,047	35,634	46,146

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. Relatively democratic countries are measured as being above the median of the Polity index. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Table A.52: Effects of mine openings in relatively less democratic countries.

	Bribes		Perceptions of Corruption	
	(1) Police	(2) Permit	(3) Local Councilors	(4) Police
Active 50 km	0.018	0.014	−0.039	0.001
	(0.763)	(0.661)	(−1.167)	(0.046)
Inactive 50 km	−0.030	0.011	−0.178	0.079
	(−0.995)	(0.192)	(−1.894)	(1.047)
Difference in differences	0.048	0.003	0.139	−0.078
F-test: active-inactive=0	1.798	0.002	1.998	0.946
p-value, F-test	0.180	0.966	0.158	0.331
Mean dep. var	0.315	0.283	1.397	1.809
R-squared	0.043	0.039	0.103	0.067
No. of observations	32,702	32,724	21,619	30,468

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. "Diff-in-diff" tests are presented in bottom rows. All regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. Less democratic countries are measured as being below the median of the Polity index. See notes to table A.3 for information on Afrobarometer waves and sample construction.

A.9 Instrumental variable models

As discussed in the section on endogenous resource extraction in the paper, despite our difference-in-differences design alleviating concerns of endogeneity bias due to mines being located in particular areas, one could still worry that the timing of the mine start-up is driven by corruption. This would bias the estimation of our baseline specification, although we discuss in the paper how the most plausible bias (withholding opening because of rampant corruption, or expected spikes in corruption) would contribute to pulling our estimates towards zero. Nonetheless, we try to further mitigate such sources of endogeneity bias by identifying possible instruments and employing 2SLS models. This has its own challenges, in terms of coming up with instruments that are both strong and satisfy the exclusion restriction.

We experimented with different ideas for instruments, for instance trying out different leads and lags of mineral-specific world market prices that *could* inform/conform with mining companies' expectations of prices when deciding whether or not it seems profitable to open a mine. However, these first-stage regressions were unable to sufficiently precisely predict active mines/mine openings (in line with what one would expect from the standard "random walk theory" of market behavior, suggesting it is difficult for economic agents to precisely predict prices), leaving us with weak instruments. We were, more generally, unable to predict the event of mine openings in our various first-stage regressions (in a sense corroborating the assumption that these timing decisions are more random than location decisions, as we discuss in the paper). Still, we were able to find instruments that predict active mines in a region with a sufficient level of accuracy, and we therefore present results from these 2SLS regressions with instruments for the "active" status of a respondent. To the extent that the exclusion restriction is not violated—which is hard to ensure completely, though we have some level of confidence that this is not too problematic here, at least when conditioning on the covariates, notably including country- and year-fixed effects (capturing, e.g., any economic or governance trends)—these 2SLS regression should provide consistent estimates of the causal effect of mining activities on local corruption.

Table A.53 shows the results with four different instrumental variables, with the first stage reported in Panel B and the second stage in Panel A. We focus only on our "Bribe to police" variable here, since this is the dependent variable for which results are robust in (almost) all other specifications that we have tested. Hence, this is the dependent variable in the second-stage regressions. All regressions include the same controls as the baseline; age, age^2, education, female and urban, as well as country and year fixed effects. The results also turn out very robust in alternative models controlling also for WBGI national-level "Control of corruption" (to ensure that national corruption does not affect both the instrument and the dependent variable).

Below, we go through the various instruments and models in sequence.

Mines within 100-200 km: In the first column of Table A.53 we instrument for *active* with the *number of mines* (active and inactive) within a band of 100-200km from the respondent. This instrument serves as a proxy for favorable geological conditions for mining in the area, and should be correlated with mining activity within 0-50km from respondents. Importantly, we exclude the band 50-100km (even though this would probably have further strengthened the instrument), to alleviate concerns that corruption spillovers could introduce biases in our results (as noted, the results hold when we also control for national corruption, and we provide further empirical tests suggesting that large-distance spillovers are not a problem at the end of this section).

The first stage result for the instrument is positive, as expected, and it is highly significant with a t-value of 22.9. In the second stage we obtain a positive and significant ($t = 5.3$) coefficient on the active dummy, and, reassuringly, with a magnitude comparable to that found in our baseline estimations. In the second column we draw on the same underlying idea in an alternative specification, using as instrument a dummy for having *at least one* mine within 100-200km (instead of the number of mines). The results hold up also in this specification; $t = 10.4$ for the dummy instrument in the first stage, and $t = 2.3$ for active in the second stage.

Mineral presence interacted with mineral-year specific conditions The third instrument we test is a composite measure, described most clearly by the following summation: For each respondent in cluster i and year t, our instrument IV_{it} is given by:

$$IV_{it} = \sum_{j=1}^{n} \left(\frac{nactive_{jt}}{nmines_j} \times nwithin100\_200_{ij} \right), \tag{1}$$

where the sum runs over mineral j in the set of n distinct minerals in our mining data. *nactive* is the number of active mines with mineral j as the main mineral in year t, and *nmines* is the total number of mines of mineral j ever recorded in our data. Since year fixed effects are included in the specifications, this fraction is a proxy for the conditions for production and export of a given mineral in a given year. This could potentially capture mineral-specific technology shocks, price expectations, or other aspects related to the profitability of being an active producer of mineral j. When interacted with the mine "presence" variable *nwithin100_200* and summed over all minerals, we get a composite predictor for the probability of there being an active mine nearby in a given year. The instrument is based on the premise that respondents are more likely to live near an active mine if they (a) live in an area suitable for mining, and (b) are interviewed by the Afrobarometer survey in a year when conditions permit profitable mineral production.

The results from the 2SLS estimation of the instrument given by (1) is shown in column 3 of Table A.53. The instrument is a strong predictor of mining activity ($t = 26.0$). The second-stage result also conforms with our expectations, yielding a positive and significant active coefficient ($t = 5.3$), of similar magnitude as in column 1.

Mineral presence interacted with prices: Finally, because one might anticipate that mineral prices affect the status of mines, we instrument with a 5-year moving average of mineral price interacted with the number of mines extracting that specific mineral within 100-200km. The first stage is again very strong ($t = 19.8$), and the second stage returns an active coefficient that is positive and highly significant ($t = 3.4$).

Further discussion on instrument validity: It should be noted that we do not consider any of these instruments as perfect. One potential threat is that the exclusion restriction on the mineral presence within 100-200km component fails, due to spillovers of corruption over large distances. We can to some extent test for this, however, by running our baseline regression with the following dummy variables: Code respondents as "active" ("inactive") if they live within 200km of an active (inactive) mine, but do *not* live within 100 km of neither an active nor inactive mine. The difference in means between these active and inactive groups will be the effect on bribes to the police of opening a mine between 100 and 200km away from a respondent who a) did not previously have a mine within 200 km, and b) will not see a mine opening within 100km in the near future. If there is no significant difference in means, we can conclude that active mines far away do not affect corruption, and the exclusion restriction assumption is plausible.[4]

The result from the regression on the described dummies is presented in table A.54. The difference in means is about 1/5 of the baseline result, and the difference is not statistically significant, with a p-value of 0.342. We also note that the coefficients on active and inactive (for mines between 100 and 200km away) are both negative and statistically insignificant at all conventional levels. In sum, we conclude that the exclusion restriction assumption seems to hold, and that the IV models should provide consistent estimates of the causal effect of

[4]We acknowledge that this test requires some faith in our baseline specification, hence the "to some extent" qualification.

Table A.53: Instrumental variables regressions (2SLS)

A: Second stage	Bribe to police	Bribe to police	Bribe to police	Bribe to police
Active 50 km	0.079	0.150	0.083	0.059
	(5.325)	(2.301)	(5.331)	(3.402)
Mean dep. var	0.225	0.225	0.225	0.225
No. of respondents	92,762	92,762	92,762	92,762
B: First stage	Mines 100-200km	>0 mines 100-200km	Share active	Price interaction
nwithin100_200	0.009			
	(22.925)			
d_nwithin100_200		0.126		
		(10.349)		
sactive_nwithin			0.018	
			(25.969)	
priceXpresence				0.078
				(19.767)
R-squared	0.390	0.301	0.385	0.364
No. of respondents	92,762	92,762	92,762	92,762

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All first- and second-stage regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

mining activities on local corruption.

Overall, the results in Table A.53 are reassuring also in the sense that we identify very similar results for different instruments, *and*, not the least, that the results from these models also strongly resemble the results from our baseline estimation.

Table A.54: Testing for spillovers

	(1) Bribe to Police
Active within 200 km, but not within 100 km	−0.004
	(−0.505)
Inactive within 200 km, but not within 100 km	−0.019
	(−1.367)
Difference in differences	0.015
F-test: active-inactive=0	0.902
p-value, F-test	0.342
Mean dep. var	0.225
R-squared	0.076
No. of observations	92,762

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. Respondents coded as "active" if they live ≤ 200 and > 100 km from an active mine, and there are no active or inactive mines within 100 km. See notes to table A.3 for information on Afrobarometer waves and sample construction.

A.10 Mechanisms: Elaborating on the nighttime light data and measure, and tables with additional tests pertaining to the four mechanisms

As described in the paper, some of our theoretical expectations relate to the relationship between mineral extraction, economic activity, and corruption. To get a measure of economic activity at the local level, we use satellite-retrieved data on light emissions at night, and map these data to our 50km buffers around respondents. In this section, we elaborate on the data and present tests relevant for the different mechanisms (that are not contained in Table 3 of the paper).

A.10.1 Nighttime light data and measures

Our measure of nighttime light is from satellite images from the US Air Force. The satellites circle the Earth each night and record earth-based lights using their Operational Linescan System for grid cells of 30 arc-seconds (corresponding to approximately 1 km^2). Several recent studies have provided empirical evidence showing that nighttime light corresponds well to economic activity and well-being (see e.g., Alesina, Michalopoulos and Papaioannou (2015), Almås, Johnsen and Kotsadam (2014), Chen and Nordhaus (2011), Doll, Muller and Morley (2006), Ghosh et al. (2010), Henderson, Storeygard and Weil (2012), Keola, Andersson and Hall (2015), Klemens, Coppola and Shron (2015), Michalopoulos and Papaioannou (2013), Pinkovskiy and Sala-i Martin (2014), and Sutton, Elvidge and Ghosh (2007)). Hence, we have a very local measure of economic activity that varies over time.

Starting from 1992, data have been digitized and made publicly available. In order to measure human-generated light, the light data is filtered by purging away observations with forest fires, auroral activity, cloud cover, and those from months when the sun sets late. The valid data points for each grid cell for each year are averaged, and the final measure is a yearly nighttime light measure ranging from zero (no light) to 63. The censoring of the data at 63 has little impact in analyses of Africa, as very few grid cells have such a high value. In total, we use data from six different satellites between the years 1992 and 2010, with partial overlap across years, so that we have 31 datasets in total. We use all the observations we have for the different satellites in our analysis. For a more detailed description of the satellite light data, see NOAA (2013).

In order to make the analysis comparable to our main analysis we combine the geocoded data from the Afrobarometer with the nighttime light data. From each Afrobarometer cluster point, given by its GPS coordinates, we create buffer zones in terms of concentric circles with a radius of 50 kilometers. We also exclude all water areas (sea and lakes) as people do not live on the water and since there are "glooming effects" of water bodies (Pinkovskiy, 2013). Figures A.3 and A.4 shows buffer zones of 50km around the mines and nighttime light in 1992 and 2010 respectively (when looking very carefully at the two maps one may even see that there seems to be increased light within the mining areas from 1992 to 2010).

We then proceed to calculate zonal statistics for the Afrobarometer areas for each year and each satellite for which we have luminosity data. The zonal statistics we calculate using ArcGIS are the median amount of light (used for the baselines reported in Table 3 in the paper) and average amount of light (used for the robustness tests in Table A.56) within each buffer zone. Finally, as there are several observations in some years, we take the average for each year. Based on these data we are able to integrate local economic activity into the same framework as the rest of our analysis.

A.10.2 Additional results using nighttime light data

In this section, we report a set of alternative specifications using the nighttime light data. To briefly recapitulate from the paper, we find support for the mining-specific version of what we term the "supply-side mechanism" (local officials, due to increased local mining income, have stronger incentives and are better capable of requiring bribes), but not for the general version assuming that mining activities and income are similar to other activities in terms

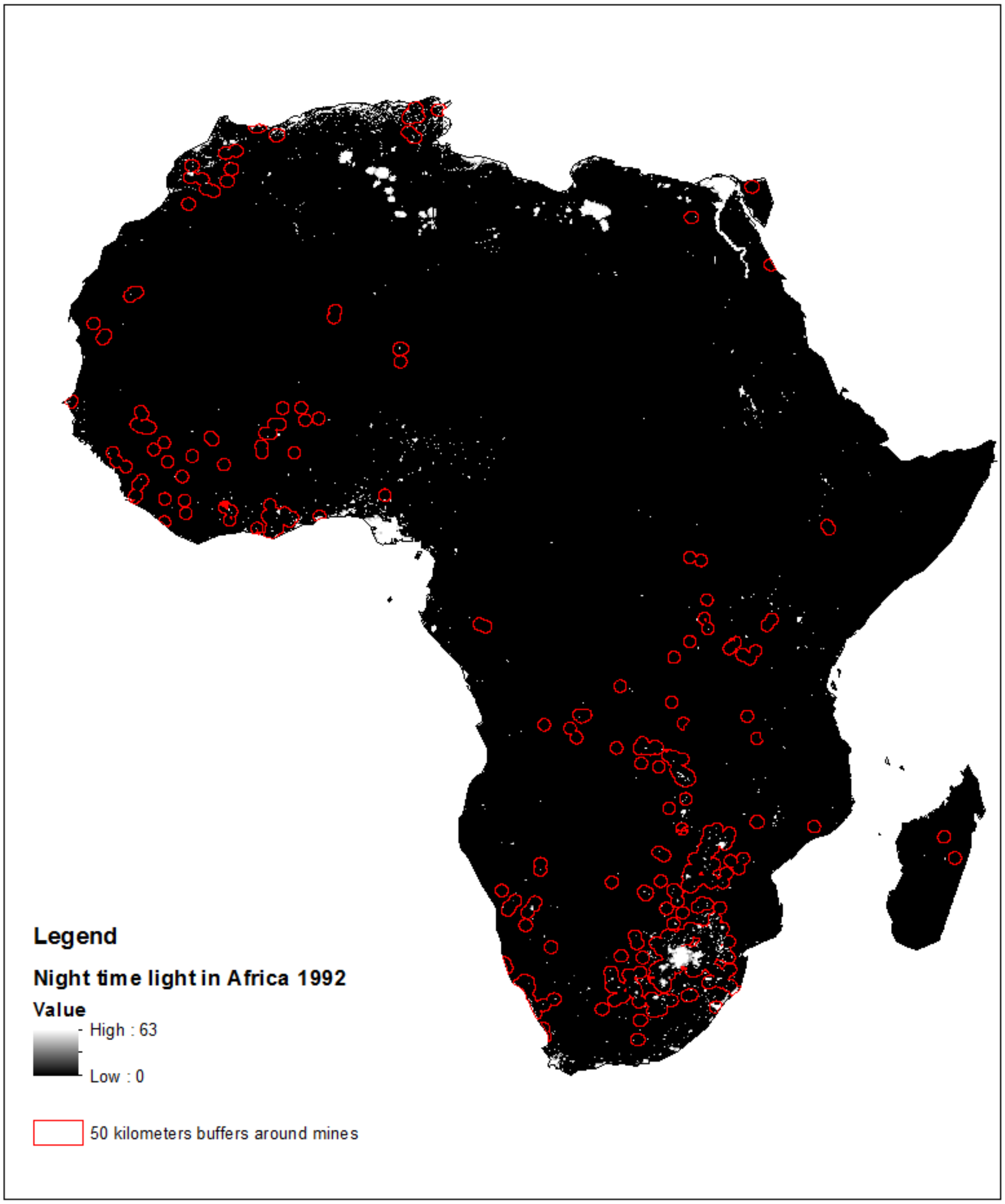

Figure A.3: Light in 1992 and buffer zones around mines

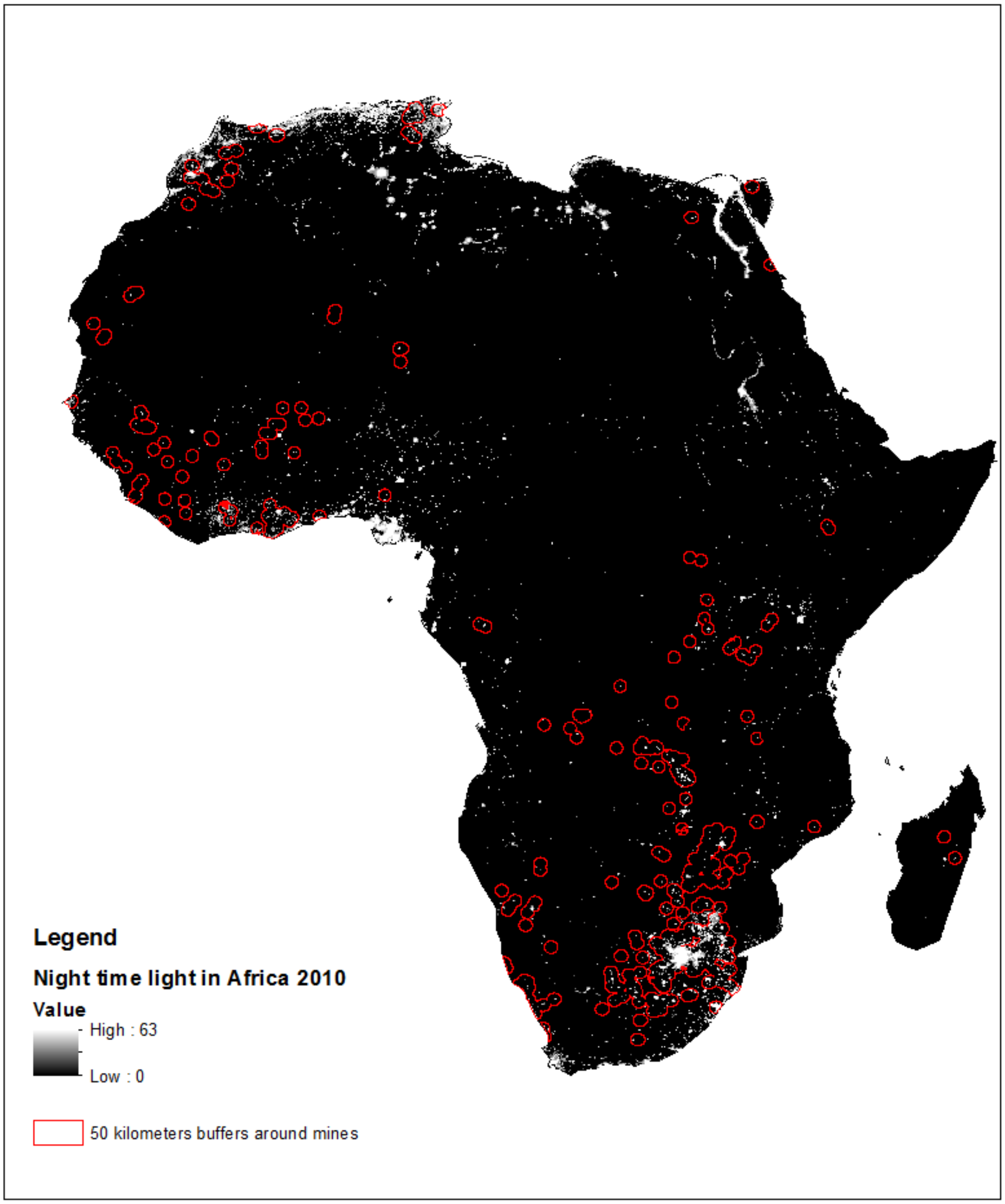

Figure A.4: Light in 2010 and buffer zones around mines of generating corruption. In the paper, we use an interaction set-up when investigating the mining-specific version of the supply-side mechanism. Table A.55 provides an alternative way to assess it, showing split sample results (for active mining areas and areas without active mines). As discussed in the paper, we observe a negative correlation between economic activity and bribes in areas without active mines. This is not the case in areas with active mines, where the point estimate is positive but not statistically significant at conventional levels (we refer to the empirical section on mechanisms in the paper for the discussion of why this might be the case). This clear difference between the two samples comports with the mining-specific supply mechanism, whereby there is something "special" about economic activity relating to the mining sector in terms of engendering corruption.

Table A.55: Correlation between median light intensity and corruption in active mining areas and areas without active mines

	(1) Bribe to Police in active areas	(2) Bribe to Police in non-active areas
Median light	0.0011	−0.0070
	(1.052)	(−3.716)
Mean dep. var	0.180	0.207
R-squared	0.106	0.246
No. of observations	1,626	5,231

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction. By "non-active areas", we mean areas without active mines (i.e., either non-mining areas or inactive mining areas).

To further evaluate and assess the robustness of the regressions using light data, we report some additional results in Table A.56. In column 1 we show the baseline model (on the net effect of mine openings on corruption), but now run on the reduced sample of collapsed clusters that only include the same observations as in the comparable regressions with nighttime lights. The sample is smaller as we only have nighttime light data until 2010. This shows that a) the results are fairly similar in this reduced sample, and b) that

Table A.56: Additional results using nighttime lights

	(1) Bribe to Police	(2) Mean light	(3) Bribe to Police	(4) Bribe to Police	(5) Bribe to Police
Active 50 km	0.0583	2.9041		0.0595	0.0420
	(6.510)	(11.369)		(6.665)	(3.866)
Inactive 50 km	−0.0431	2.2022		−0.0422	
	(−3.392)	(5.590)		(−3.294)	
Average light			0.0001	−0.0004	−0.0030
			(0.201)	(−0.656)	(−3.531)
Average light × Active 50 km					0.0035
					(3.413)
Difference in differences	0.101	0.702		0.102	
F-test: active-inactive=0	53.783	2.511		54.428	
p-value, F-test	0.000	0.113		0.000	
Mean dep. var	0.200	4.245	0.200	0.200	0.200
R-squared	0.209	0.439	0.203	0.209	0.209
No. of observations	6,857	6,858	6,857	6,857	6,857

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

the results with and without controls for light are very similar (when comparing to column 4). In column 2 we show that mine openings seemingly lead to more economic activity, also when it is proxied by *average* nighttime light, although the result is weaker than for the *median* light specification we use in the paper (p-value for the F-test is 0.11 when using average light). As with median light, average light is not correlated with bribe payments in general (column 3) and controlling for average light does not alter the results (see column 4). Column 5 presents the interaction results with average luminosity, and we again note a similar pattern as in the main analysis presented in Table 3 of the paper.

A.10.3 Results for the Afrobarometer interviewer having observed police officers or police stations in the area

In the paper, we also discussed what we termed the "demand mechanism" on mining activity attracting corrupt officials to the area (again separating between a general and a mining-specific version). As noted, we use Afrobarometer items on whether the interviewer him/herself noted the presence of police officers or police stations in the Primary Sampling

Table A.57: Police presence and police bribes

	(1) Bribe to Police	(2) Bribe to Police
Police in area	0.034	
	(5.140)	
Police station in area		0.022
		(3.356)
Mean dep. var	0.225	0.225
R-squared	0.078	0.078
No. of observations	91,824	90,800

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

Unit. While the tables further below show that there is no clear evidence supporting the demand mechanism (with some caveats for the mining-specific version), Appendix Table A.57 at least shows that observed police officials and police stations systematically correlate with reported police bribes, as expected.

Appendix Table A.58 (columns 1 and 2) shows that police stations and officers are more often spotted in mining areas; *active* is positive and with $t = 1.8$ both for police officers *and* for police stations. But, we do not find that mine openings generate more interviewer observations of police officials or stations, as the difference is not statistically significant and the point estimate is even negative. Further, columns 3 and 4 show that controlling for stations or officers, respectively, does not reduce the estimated effect of a mine opening on police bribes.

Regarding the expectations for the general version of the mechanism, we see that that economic activity in general (as measured by nighttime light) does not correspond with observed police officials or stations (columns 1 and 2 of Appendix Table A.59). Appendix Table A.59 also shows results pertaining to the mining-specific version. Supporting this version, column 3 shows that nighttime light and police official presence correlate positively in mining areas, even though the result falls short of conventional levels of significance ($t = 1.5$),

Table A.58: Mining and police presence

	(1) Station	(2) Officer	(3) Bribe to Police	(4) Bribe to Police
Active 50 km	0.026	0.024	0.021	0.021
	(1.823)	(1.835)	(2.635)	(2.592)
Inactive 50 km	0.074	0.059	−0.056	−0.056
	(2.162)	(1.784)	(−4.237)	(−4.198)
Police station in area				0.022
				(3.362)
Police in area			0.034	
			(5.142)	
Difference in differences	−0.049	−0.035	0.076	0.077
F-test: active-inactive=0	1.992	1.135	30.903	30.086
p-value, F-test	0.158	0.287	0.000	0.000
Mean dep. var	0.335	0.301	0.225	0.225
R-squared	0.188	0.183	0.078	0.078
No. of observations	91,565	92,599	91,824	90,800

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction.

and column 5 that they are negatively related in non-mining areas ($t = -2.9$). However, columns 4 and 6 show that this pattern does not hold when substituting interviewer-observed police officers with observed police stations.

Table A.59: Economic activity and police presence

	All		Active mine areas		Non-active mine areas	
	(1) Officer	(2) Station	(3) Officer	(4) Station	(5) Officer	(6) Station
Median light	0.0007	−0.0001	0.0023	−0.0014	−0.0096	−0.0036
	(0.525)	(−0.056)	(1.508)	(−0.872)	(−2.856)	(−1.056)
Mean dep. var	0.332	0.352	0.428	0.474	0.303	0.316
R-squared	0.170	0.187	0.129	0.187	0.178	0.174
No. of observations	6,776	6,665	1,575	1,538	5,201	5,127

Notes: Standard errors are clustered at EA/town level and t-statistics are in parentheses. All regressions control for country- and year-fixed effects, urban area, age, age^2, female and education. See notes to table A.3 for information on Afrobarometer waves and sample construction. By "non-active mine areas", we mean areas without active mines (i.e., either non-mining areas or inactive mining areas).

A.11 Mine openings and national-level corruption

This section presents suggestive evidence as to whether the results found for local corruption aggregate to corruption at the national level. To investigate this, we perform two types of tests. First, we run models regressing the "Control of Corruption" measure from the WBGI (Kaufmann, Kray and Mastruzzi, 2010) on a simple measure counting the absolute number of mines that opened in a country in a given year. The first model includes year-fixed effects while the second adds country-fixed effects. The results from these two regressions are reported in Table A.60. In both models, we find positive coefficients, but the coefficient only reaches a weak level of significance when including country-fixed effects (t-value=1.82). Hence, there is some evidence that mine openings relate not only to local-level, but also national-level corruption as measured by the WBGI, although the latter result is not very robust. (We also remark that these national-level regressions include countries such as Angola and DR Congo, where extant studies suggest that mining has been linked to poor governance outcomes, not included in our local-level regressions due to lack of Afrobarometer data).

To probe this further, we run a second set of models, shown in Table A.61, where we regress the simple *national average* of our local-level Afrobarometer corruption measures on the number of mines opened in a country in a given year. We note that these results draw on significantly fewer country-year observations (only the countries and years covered by the Afrobarometer). In these models, we find weak and mixed results. For example, the estimated relationship is negative (though insignificant) in the model on bribes paid to the police, and positive (and insignificant) in the model on bribes for permits. In summary, we are unable to identify a clear effect when employing aggregated national-level measures. It should be noted however, that the analyses mentioned here are tentative (e.g., due to them relying on "naive" aggregates of national-level corruption), given that our main focus has been put on investigating local corruption. Still, as we address in the literature review of the paper, numerous extant studies have already employed different measures of national-level corruption coupled with various national-level resource measures, and the reported results—as is the case for results in this sub-section—are mixed. A more in-depth analysis of the link between national-level corruption and mining would need to think more carefully about how to properly aggregate mining variables to the national level and properly capturing national-level corruption. Perhaps even more important, it would also need to address endogeneity issues in ways equally satisfactory as our local-level design.

Table A.60: Mine openings and national corruption: WBGI

	WBGI Control of corruption	
	(1) OLS	(2) Fixed effects
No. of mines opened	0.095	0.020
	(3.442)	(1.823)
Mean dep. var	−0.545	−0.545
R-squared	0.049	0.012
No. of observations	490	490

Notes: Standard errors are conventional and t-statistics are in parentheses. Due to a small number of clusters (35), clustering gives a biased estimate of standard errors (Angrist and Pischke, 2008). In this case clustered standard errors were smaller than conventional, and we therefore report the largest of these to be conservative. All regressions control for year-fixed effects. National corruption is measured using the "control of corruption index" from the WBGI.

Table A.61: Mine openings and national corruption: Afrobarometer

	Bribe to Police		Bribe for Permit		Local Corruption		Police Corruption	
	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE	(7) OLS	(8) FE
No. of mines opened	−0.017	−0.019	0.031	−0.020	0.002	0.003	0.031	−0.006
	(−1.252)	(−1.830)	(0.836)	(−0.987)	(0.173)	(0.408)	(0.930)	(−0.483)
Mean dep. var	0.237	0.240	1.299	1.574	0.237	0.240	1.299	1.574
R-squared	0.124	0.164	0.155	0.120	0.310	0.220	0.269	0.192
No. of observations	82	82	66	82	82	82	66	82

Notes: Standard errors are conventional and t-statistics are in parentheses. Due to a small number of clusters (28), clustering gives a biased estimate of standard errors (Angrist and Pischke, 2008). In this case clustered standard errors were smaller than conventional, and we therefore report the largest of these, to be conservative. All regressions control for year-fixed effects. See notes to table A.3 for information on Afrobarometer waves and sample construction.

References

Afrobarometer Data. N.d. Round 2–5, 2002, 2003, 2004, 2005, 2006, 2008, 2009, 2011, 2012, 2013.

URL: *http://www.afrobarometer.org*

Alesina, Alberto, Stelios Michalopoulos and Elias Papaioannou. 2015. "Ethnic Inequality." *Journal of Political Economy* (Forthcoming).

Almås, Ingvild, Åshild Auglænd Johnsen and Andreas Kotsadam. 2014. "Poverty in China seen from outer space.".

Altonji, Joseph G, Todd E Elder and Christopher R Taber. 2005. "Selection on Observed and Unobserved Variables: Assessing the effectiveness of Catholic schools." *Journal of Political Economy* 113(1):151–183.

Angrist, Joshua D and Jörn-Steffen Pischke. 2008. *Mostly harmless econometrics: An empiricist's companion.* Princeton: Princeton University Press.

Chen, Xi and William D Nordhaus. 2011. "Using Luminosity Data as a Proxy for economic Statistics." *Proceedings of the National Academy of Sciences* 108(21):8589–8594.

Deconinck, Koen and Marijke Verpoorten. 2013. "Narrow and scientific replication of "The slave trade and the origins of mistrust in Africa." *Journal of Applied Econometrics* 28(1):166–169.

Doll, Christopher NH, Jan-Peter Muller and Jeremy G Morley. 2006. "Mapping regional economic Activity from Night-time Light Satellite Imagery." *Ecological Economics* 57(1):75–92.

Ghosh, Tilottama, Rebecca L Powell, Christopher D Elvidge, Kimberly E Baugh, Paul C Sutton and Sharolyn Anderson. 2010. "Shedding Light on the global Distribution of economic Activity." *The Open Geography Journal* 3(1).

Gilmore, Elisabeth, Nils Petter Gleditsch, Päivi Lujala and Jan Ketil Rød. 2005. "Conflict diamonds: A new dataset." *Conflict Management and Peace Science* 22(3):257–272.

Henderson, J Vernon, Adam Storeygard and David N Weil. 2012. "Measuring Economic Growth from Outer Space." *The American Economic Review* 102(2):994.

Imbens, Guido W and Donald B Rubin. 2015. *Causal Inference in Statistics, Social, and Biomedical Sciences*. Cambridge University Press.

Kaufmann, Daniel, Aart Kray and Massimo Mastruzzi. 2010. "The Worldwide Governance Indicators. Methodology and Analytical Issues." World Bank Policy Research Working Paper 5430.

Keola, Souknilanh, Magnus Andersson and Ola Hall. 2015. "Monitoring economic Development from Space: using Nighttime Light and Land Cover Data to measure economic Growth." *World Development* 66(2):322–334.

Klemens, Ben, Andrea Coppola and Max Shron. 2015. "Estimating Local Poverty Measures Using Satellite Images." *World Bank Policy Research Working Paper Series* 7329.

Lujala, Päivi, Jan Ketil Rød and Nadja Thieme. 2007. "Fighting over oil: Introducing a new dataset." *Conflict Management and Peace Science* 24(3):239–256.

Lujala, Päivi, Nils Petter Gleditsch and Elisabeth Gilmore. 2005. "A diamond curse? Civil war and a lootable resource." *Journal of Conflict Resolution* 49(4):538–562.

Michalopoulos, Stelios and Elias Papaioannou. 2013. "Pre-Colonial Ethnic Institutions and Contemporary African Development." *Econometrica* 81(1):113–152.

NOAA. 2013. "DMSP-OLS Nighttime Lights Time Series Version 4." National Geophysical Data Center, Earth Observation Group.
URL: *http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html (accessed August 19, 2013)*

Nunn, Nathan and Leonard Wantchekon. 2011. "The Slave Trade and the Origins of Mistrust in Africa." *American Economic Review* 101(7):3221–3252.

Oster, Emily. 2013. "Unobservable selection and coefficient stability: Theory and validation.".

Pinkovskiy, M. 2013. "Economic Discontinuities at Borders: Evidence from Satellite Data on Lights at Night.".

Pinkovskiy, Maxim and Xavier Sala-i Martin. 2014. "Lights, Camera,... Income!: Estimating Poverty Using National Accounts, Survey Means, and Lights." *Working paper* .

Ross, Michael L. 2012. *The Oil Curse: How Petroleum Wealth Shapes the Development of Nations*. Princeton: Princeton University Press.

SNL Metals and Mining. 2014. "Raw Materials Database.".

Sutton, Paul C, Christopher D Elvidge and Tilottama Ghosh. 2007. "Estimation of Gross Domestic Product at Sub-national Scales using Nighttime Satellite Imagery." *International Journal of Ecological Economics & Statistics* 8(S07):5–21.

Teorell, Jan and Stefan Dahlberg and Soren Holmberg and Bo Rothstein and Felix Hartmann and Richard Svensson. 2015. "The Quality of Government Standard Dataset, version Jan15.".