AIDDATA
A Research Lab at William & Mary

WORKING PAPER 66

December 2018

Priming the Pump: Does Aid Pave the Way for Investment?

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Abstract

Recent advances in the coverage and precision of development data have opened exciting new avenues for analyzing the political economy behind the allocation and effectiveness of foreign aid. While a number of recent papers have looked at the social, environmental or welfare implications of aid, this paper instead focuses on how aid impacts an intermediate outcome in the development process, foreign direct investment (FDI). Combining geo-referenced data on foreign aid with a similarly coded dataset of FDI project locations, the paper uses a quasi-experimental, spatial-temporal, identification strategy to evaluate if the location of foreign aid projects presages later FDI. Drawing on the literature on the political economy of aid, the paper develops theoretical expectations about a given donor's aid and FDI projects from that state before finding that local aid increases the chance of a location attracting FDI by up to 40 percent. While aid and FDI from bilateral donors goes hand-in-hand, both Chinese and EU aid also attracts FDI from other sources.

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Acknowledgements

The author thanks the European Union's Horizon 2020 research and innovation programme under grant agreement number 693609 (GLOBUS) for generous funding support for this project. Comments/critiques/ suggestions welcomed.

Introduction

The geo-spatial revolution in development data has facilitated the rise of new research agendas which consider the political economy of subnational and local aid allocation and impact. Recent studies have used geo-referenced data to consider questions of aid's local impact on topics including growth, welfare, the environment, and governance (Dreher and Lohmann 2015, Bizter and Goren 2018, Blair and Roessler 2018, Martorano et al. 2018). Other work has considered the political motivations behind sub-national allocation of aid (Briggs 2017). This paper also takes advantage of precisely-located aid projects to investigate if and how aid can serve as a precursor for foreign direct investment (FDI). While a number of papers have evaluated the aid-FDI relationship at the cross-national level, there are few that theorize or test the relationship at a local level. This paper contends that aid can often lay the local groundwork for FDI by providing the physical, if not institutional and human, infrastructure that is needed for private enterprise. However, these expectations are tempered by theorizing that these efforts may not be universal in their effects, but instead might be structured so as to facilitate source FDI primarily from the donor country. Donors that are more explicit about the strategic economic or political aims of their aid programs may be more likely to have projects that attract their own FDI.

In order to evaluate these claims, the paper utilizes several geo-coded foreign aid datasets in Africa from the AidData project combined with nearly 10,000 geo-referenced FDI project locations from the Financial Times fDi Markets database. These geo-referenced data allow employment of a spatial-temporal identification strategy that uses information on project timing and location to construct a quasi-randomized environment in which one can observe an aid treatment effect. The analysis follows a difference-in-difference approach that compares locations with *active* aid projects at the time of the first FDI project those those that do not have an active aid project, but subsequently will. Both of these sites are then compared to locations that have no aid project throughout the duration of the dataset.

The results suggest that, in general, aid is substantially effective in attracting FDI, with locations with active aid projects up to 40 percent more likely to receive a subsequent FDI project compared to sites where aid projects are not yet active. However, when looking at aid and FDI from individual source actors, the results are more nuanced. Local aid projects *from a given donor* are extremely likely to be co-located with FDI from *that* actor, but the difference between an active and inactive site is negligible, suggesting simultaneity rather than causality. Yet, active aid from some individual donors, notably China and the EU, does also appear to attract FDI from *other* countries. In contrast, aid from Japan and the US has no impact on attracting outside FDI.

Aid and FDI

A substantial amount of literature has suggested that aid may precede or facilitate FDI, including in Africa (Anyanwu 2012, Amusa et al. 2016), although aid may also simultaneously serve to crowd out FDI (Selaya and Sunesen 2012). Foreign aid can boost economic infrastructure (Donaubauer et al. 2016), serve in a signaling function, especially in post-conflict countries (Garriga and Phillips 2014), or facilitate human capital and social cohesion (Donaubauer et al. 2014, Cleeve et al. 2015, Addison and Baliamoune-Lutz 2016) which in turn attracts FDI. While most studies have suggested that the relationship between aid and FDI is positive, some have suggested this only applies for some countries (Kimura and Todo 2010, Arazmuradov 2015) while other work has found a *negative* relationship between the two (Donaubauer 2014). However, with the notable exception of Blaise's (2005) study on Japanese inflows to China, nearly all of this literature focuses on the relationship between ODA and FDI at the recipient *country* level.

As shown above, the cross-border literature suggests several pathways by which foreign aid can induce investment. When considering the link at the local level these causal mechanisms become clearer. A variety of different aid projects may increase local suitability for FDI. Most obviously, aid classified as "Aid for Trade" (AfT), may help improve local business conditions and attract FDI (Lee and Ries 2016). AfT is a broad classification and includes categories of productive infrastructure – including transportation, energy, communications and utilities infrastructure – but also can include, often industry-specific, technical training or research and development (Brazys and Lightfoot 2016). The locational link is most obvious with physical infrastructure, but it is also plausible that aid projects which upskill local labor pools will also make that location more attractive to FDI (Donabauer et al. 2014).

The existing literature is relatively agnostic regarding heterogeneity in the aid-FDI relationship, usually neglecting to consider if the *source* of aid and/or FDI may contribute to its linkage.[1] However, there is substantial reason to suspect heterogeneity in the aid-FDI relationship depending on the political economy of the source country. Considerations of foreign economic policy motivation date to at least McKinlay and Little (1977) and have

[1] Kimura and Todo (2010) who find that Japanese aid only attacts Japanese FDI being an important exception.

sustained a prolonged debate if foreign aid is given to suit "donors' interests" or "recipients' needs" (Alesina and Dollar 2000, Berthelemy and Tichit 2004), or, more subtly, if it is "targeted" for development purposes in countries most likely to engender spillovers to the donor (Bermeo 2017). Extending the logic of this literature, it is eminently plausible to think that aid from some donors may be used to facilitate FDI from that country.

While there is reason to suspect general country-level heterogeneity in the aid-FDI relationship, the empirical literature also gives clues as to country-specific expectations. As the largest foreign aid donor, the United States has long been pilloried as self-interested (McKinley and Little 1979), although the empirical findings are mixed as to the extent to US engages in purely egotistical aid allocation behavior (Brazys 2010, Harrigan and Wang 2011, Bearce et al. 2013). Likewise, the second-largest historical donor, Japan, has historically faced accusations that its aid program is driven for geo-economic reasons (Hook and Zhang 1998), particularly since official documentation is often naked in these aims and indeed Japan has been criticized for use of tied aid as an extension of "Japan Inc." (Hall 2011). Indeed, both country-level and sub-national studies have suggested that (only) Japanese FDI follows Japanese ODA (Blaise 2005, Kimura and Todo 2010). In contrast, the EU is often portrayed as a "normative power" driven by more altruistic aims, although, again, the evidence here is mixed (Carbone 2013, Brazys 2013). Indeed, in the case of the EU, this may be driven by the internal incoherence of the EU's "shared competence" with member states in development policy.

Outside the traditional donors of the OECD's Development Assistance Committee (DAC), China has recently emerged as a major actor in the development space. Once again, there is a popular perception that Chinese development efforts are primarily intended to help China, and indeed there is some evidence that Chinese aid flows increase Chinese FDI flows to the same country (Su et al. 2017). However, the empirical evidence is again mixed, with some work suggesting that Chinese aid is effective in boosting growth (Dreher et al. 2017), while other work suggests Chinese development efforts may undermine local governance (Brazys et al. 2017, Isaksson and Kotsadam 2018) or traditional donors' conditionality efforts (Hernandez 2017). To shed light on this heterogeneity, the empirical section below not only examines the general relationship between aid and FDI, but also considers actor-specific relationships for the US, EU, Japan and China.

Data and Methods

The primary outcome variable is greenfield and expansion FDI projects drawn from the Financial Times fDI markets database, which has been used in a number of recent studies in economic and political science (Gil-Pareja et al. 2013, Brazys and Regan 2017, Owen 2018). This data includes not only data on project characteristics (size, sector) but also geographic data on source country and project location. This study considers 9,864 projects in fifty-six African countries from 2003 to 2017. Of these, 6,133 project records contain geographic destination at the city-level, and accordingly the analysis uses these to identify local effects. While the data does include information on project size, both in terms of investment amount and job creation, the bulk of this is estimated, and potentially biased.[2] Accordingly, this paper relies on project counts as this data is verified and cross-referenced in the original fDi Markets methodology.

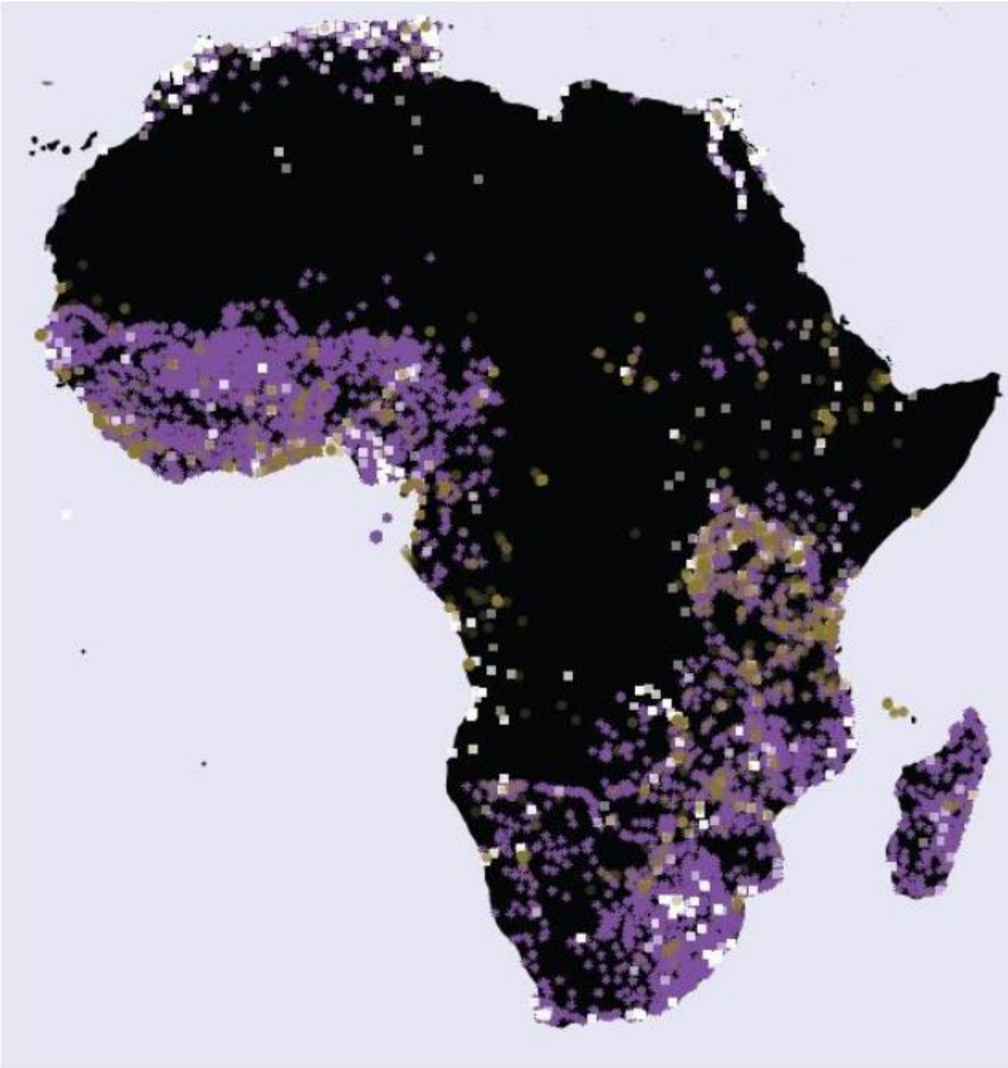
The primary explanatory variables come from AidData's geo-coded datasets. In the primary analysis, the paper relies on seven country-level "Aid Information Management System" (AIMS) datasets from Burundi, Democratic Republic of the Congo, Malawi, Nigeria, Senegal, Sierra Leone and Uganda (Peratsakis et al. 2012; AidData 2016a; AidData 2016b; AidData 2016c; AidData 2016d; AidData 2017a; AidData 2017b). These datasets capture geo-referenced aid projects from most OECD donors as well as the World Bank. This data is combined with similar project-level, geo-coded, data on Chinese development efforts (Strange et al. 2017). The primary analysis considers projects in that data coded as "ODA-like." In the robustness checks, Africa-wide data for both Chinese and World Bank aid is also used. Collectively, these data cover 2,633 projects at 4,315 locations from 2000 to 2014. Map 1 displays the spatial locations of the AfroBarometer respondents (purple stars), ODA projects (white squares) and FDI projects (gold circles).

In order to conduct the empirical analysis, the paper takes advantage of both spatial and temporal dimensions of the data in order to employ a quasi-experimental, difference-in-difference, approach similar to that used in Knutsen et al. (2017). First, the paper uses spatial information to identify sites that are in proximity to aid and/or FDI projects. In the primary analysis, the paper utilizes enumeration areas from the geo-coded AfroBarometer surveys as the site locations (BenYishay et al. 2017). AfroBarometer sites have the distinct advantage of facilitating the use of site-specific governance variables, in particular local experience with and perceptions of corruption, both of which have been shown to be correlated with local FDI (Brazys and Kotsadam 2018). The caveat of this approach,

[2] Brazys and Kotsadam (2018) who also use this data find a significant difference in the total amount of FDI calculated via the fDi Markets data when compared to official World Bank statistics.

however, is that the location of Afrobarometer enumeration sites could be endogenous to aid or FDI project siting. As such, the interpretation of the main results is a comparison of the likelihood that aid attracts FDI *at Afrobarometer sites*. To address this caveat, and look for more generalizable impact, grid-cells are used as the base locations in the robustness checks below.

Map 1: FDI, Aid and AfroBarometer Respondent Locations



The analysis next takes advantage of the fact that both the aid and FDI project records indicate the timing of projects. This information is used to identify site locations where an aid project was *active* at the time the first FDI project began as well as *inactive* sites where an aid project would begin *after* the first FDI project. Both of these sites are then compared to sites with no aid project at any time. This approach enables a mitigation of endogenous selection effects, that is that there is some additional characteristic(s) of a particular site that makes it attractive to *both* aid and FDI. By taking a difference-in-difference between active and inactive sites, the paper can evaluate the impact of an aid project "treatment" on the likelihood that a site attracts FDI. In reduced form:

$$(1) \quad Y_{it} = \beta_1 \cdot active_{it} + \beta_2 \cdot inactive_{it} + \alpha_s + \delta_t + \gamma \cdot \boldsymbol{X}_{it} + \varepsilon_{ivt}$$

where the first FDI outcome *Y* for site location *i* at year *t* is regressed on dummy variables *active* and *inactive* for aid projects at the time of the FDI outcome. The models below control for both country (α_s) and year (δ_t) fixed effects and use robust standard errors. The models below also control for a vector $(\mathbf{X}_i)$ of site-level control variables aggregated from individual responses the Afrobarometer. The baseline set are perceptions of corruption of government officials as a measure of local governance quality and an urban/rural indicator for the respondent site. The results are checked for robustness against no controls and expanded controls below.

Analyses using a spatial identification approach similar to the one here have to make an assumption about the geographic reach of the treatment. This is ultimately an empirical question that includes a trade-off between the precision of the geo-location in the data, noise, and the size of the treated unit, which in this case is a polygon. The analysis employs precision code "2" in the AidData, which is "city-level" like the FDI data, or precise to roughly 25km. Accordingly, a cut-off off less than 25km is not justifiable given the precision of the data. Most studies using this approach have settled on 50km as the ideal distance for evaluation (Knutsen et al. 2017, Brazys and Dukalskis 2017, Brazys and Kotsadam 2018) and the primary analysis below uses that distance. However, 25km and 75km treated distances are also examined, with the expectation that there is a dilution of the treatment effect as the distance is increased.

Results

The results from the combined model are available in Table 1. The hypothesis that aid attracts FDI is strongly supported. In the 50km Model (2), sites with an active, proximate, aid project within 50km are 27.1 percent more likely to attract at least one FDI project compared to sites where there is no active aid project but that will eventually get an aid project. This magnitude is quite substantive and is strongly suggestive that aid presages FDI. The difference-in-difference is significant at the 1% level. The negative sign and significance of the coefficients, particularly on *inactive*, is also of interest, suggesting that sites which will receive aid projects are *less likely* than non-aid sites to receive an FDI project. One interpretation of this result is that aid goes to otherwise “disadvantaged” sites, suggesting that it is appropriately targeted to areas of need. As the coefficient on *active* is still negative, it suggests that aid does not completely eliminate this disadvantage, but does reduce it significantly. The 25km (Model 1) and 75km (Model 3) results are consistent with the expectation that the treatment effect reduces in distance. While difference-in-difference for the 25km result is both of a larger magnitude and increased statistical significance, the difference-in-difference for the 75km result is smaller and not statistically significant.

Table 1: All Donors in African AIMS Countries

VARIABLES	(1) 25 km	(2) 50 km	(3) 75 km
Active	-0.038	-0.137*	-0.377***
	(0.052)	(0.072)	(0.066)
Inactive	-0.447***	-0.408***	-0.318***
	(0.125)	(0.073)	(0.075)
Observations	1,371	1,371	1,371
R-squared	0.262	0.234	0.259
Baseline controls	YES	YES	YES
Year FE	YES	YES	YES
Country FE	YES	YES	YES
Difference in difference	0.409	0.271	-0.059
F test: active-inactive=0	9.244	7.191	0.364
p value	0.002	0.007	0.546

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

While the general hypothesis is unambiguously supported, the source-actor results reveal more nuance. When considering the impact of source actor aid on source actor FDI (Models 1, 3, 5 and 7) there is no increase in FDI for *active* aid sites compared to *inactive* sites. However, in all cases, there is strong correlation between aid and FDI projects from a given source actor at a given site, as seen by the large and positive coefficients on both *active* and *inactive*. In all instances, the probability that a site with active or inactive aid from a source actor also gets an FDI project from that source actor is at least 0.56, and in the case of Japan (Model 5) and China (Model 7), around 0.8. This is strongly suggestive that aid and FDI from a given source go hand-in-hand, with neither causing the other. Instead, a plausible interpretation is that donors focus on particular sites and direct both aid and investment to that area. There is little variation across the donors in the outcome, although the correlations are slightly larger for both Japan and China.

Interestingly, however, in two cases aid from a given donor *does* appear to increase FDI from *other* sources. Aid from both the EU (Model 4) and China (Model 8) leads to a positive difference-in-difference that is significant at the 1% level. In both instances the magnitude is larger than Model 2 in Table 1, with EU aid leading to a 35.7 percent increase in the likelihood of FDI and Chinese aid increasing the likelihood of a non-Chinese FDI project by 41.4 percent. In contrast, aid from the US and Japan leads to no statistically significant increase in the likelihood of an *active* site receive outside FDI. These results are consistent with the literature above which suggests that the US and Japan may be more self-interested donor agents, while the EU is more normative in its actions. The China result is also consistent with building evidence that Chinese aid is broadly conducive to (immediate) economic growth (Dreher et al. 2017).

Robustness

This section subjects the results above to a number of robustness checks. The full tables of results can be found in the supplementary online appendix. The first check is to cross-validate the result on a larger sample. AidData has geo-coded, project-level information for Chinese and World Bank projects in all African countries. Accordingly, the analysis is expanded to all of these locations, both with aggregated aid projects and via examining the World Bank and China separately. The substantive results are maintained, with combined Chinese and World Bank aid (Model S1) leading to a positive difference-in-difference in *active* aid sites attracting FDI compared to *inactive* sites. However, the magnitude of results above are only maintained for World Bank aid (Model S2) which increases *active* sites chances of attracting FDI by 41.7 percent, a difference-in-difference significant at the 1% level. While the difference-in difference of Chinese aid projects (Model 3) is positive and significant at the 5% level, the magnitude is considerably smaller than the result from the AIMS countries subsample (Model 8).

Second, the paper includes different sets of site-levels controls as well as lagging the aid projects. Aid effectiveness literature has suggested that aid projects, particularly infrastructure, may take some time to be realized (Brazys 2010; Bearce et al. 2013). Accordingly, it may take some passage of time before a site becomes more attractive to FDI and as such the robustness checks explore several lags (Models S4-S6). Likewise, to check the robustness of the results, a model with no controls (S7), as well as a model with additional controls (S8), including other measures of local corruption, including local corruption perceptions of police, judges, tax officials, and MPs as well as local corruption experiences of paying bribes for permits or to the police, measures of average household cash flows, and reported experienced with discussing politics, are examined. The models using lags and alternative controls are all substantively similar to the main results.

Table 2: Source Country Heterogeneity in African AIMS Countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	US FDI	NonUS FDI	EU FDI	NonEU FDI	JP FDI	NonJP FDI	CN FDI	NonCN FDI
active_source	0.753***		0.558***		0.869***		0.857***	
	(0.075)		(0.033)		(0.051)		(0.034)	
inactive_source	0.682***		0.587***		0.781***		0.793***	
	(0.032)		(0.041)		(0.036)		(0.031)	
active_nonsource		-0.334***		0.019		-0.181***		-0.033
		(0.054)		(0.052)		(0.045)		(0.045)
inactive_nonsource		-0.348***		-0.338***		-0.252***		-0.447***
		(0.051)		(0.045)		(0.058)		(0.058)
Observations	1,371	1,371	1,246	1,246	1,371	1,371	1,371	1,371
R-squared	0.263	0.219	0.320	0.222	0.271	0.143	0.312	0.199
Baseline controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Difference in difference	0.071	0.014	-0.029	0.357	0.088	0.071	0.064	0.414
F test: active-inactive=0	0.793	0.035	0.338	26.085	2.305	0.987	1.774	32.815
p value	0.373	0.851	0.561	0.000	0.129	0.321	0.183	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Third, as discussed above, the primary analysis uses AfroBarometer enumeration sites from which to assess proximity to projects. While using these sites has the advantage of using aggregated, site-level, controls from that survey, the paper checks robustness of these results by using generic grid cells, which have the distinct advantage of uniformly and completely covering the spatial analysis area. The base grid-cell data comes from the International Food Policy Research Institute (IFPRI 2017) and utilizes grids spaced at five-minute distances. This data also contains variables on land usage including area of cropland, urban area, and area of water bodies. Controlling for each of these variables, the results are substantively reproduced looking at both 25km (Model S9) and 50km (Model S10) distances. Model S11 also limits the analysis to only grid cells that have evidence of habitation (crop or urban land usage), again with consistent results.

Finally, it is possible that the outcome process is spatially auto-regressive. The study of economic geography is premised on the fact that economic concerns may cluster for a variety of reasons, leading to spatial autocorrelation. This possibility is tested for by calculating Moran's I on the residuals from model II. As shown in the supplemental online appendix (Figure SA1), the spatial correlation coefficient at close proximity (bands 1-2 and 1-3) is not significantly different from the expected statistic under conditions of no spatial correlation. However, when looking further afield (bands 1-4 and 1-5) while the correlation coefficient is still quite small, it now is statistically different form the expected value, indicating the presence of spatial autocorrelation. Arguably these results are more suggestive of political boundary effects, rather than spatial autocorrelation, but as a further robustness check the specification is run using both a spatial autoregressive (SAR) (Model S12) and a spatial error model (SEM) (Model S13). In both models the difference-in-difference between *active* and *inactive* sites is significant at the 5% level and the magnitude is quite similar to that in Model 2 above. Moreover, the *p* values of rho (Model S12) and lambda (model S13) suggest that any spatial autocorrelation is sufficiently addressed by the models

Conclusions

This paper's findings convincingly suggest that aid facilitates investment. By extension, the result supports the claim that aid can facilitate local economic activity. Indeed, this finding is compatible with several recent studies which identify a local impact of aid on growth (Civelli et al. 2018; Bitzer and Goren 2018). Interestingly, the causal linkage between aid and investment doesn't hold when considering aid and FDI from the same source actor. Rather than aid causing FDI in this instance, aid and FDI from the same donor appear to go hand-in-hand, suggesting that both are driven by the same locational considerations, perhaps as a packaged approach to foreign economic policy. However, aid from two major donor actors, the EU and China, does also increase local FDI from *other* countries. In contrast, aid from the US and Japan does not attract FDI from other sources. Regardless of if the EU and Chinese results are an intended or unintended spillover from a more self-serving foreign economic policy, it is suggestive that aid can build the public goods that attract FDI.

While these findings complement recent subnational analyses that finds that “aid works”, it should be noted that nothing can be determined about local socio-economic impacts or distributive effects. Few studies have yet linked FDI to local impacts and further work in this direction is vital to understand if the aid-FDI linkage ultimately engenders positive local development outcomes.

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Supplementary Online Appendix

Table SA1: Data Sources and Summary Statistics

Variable	Variable	Source	Max	Min	Mean	Std Dev.	Observations
Cluster Level at 50km (Model 2)							
FDI		www.fdimarkets.com	1	0	0.590	0.492	1,371
Active		www.aiddata.org	1	0	0.023	0.151	1,371
Inactive		www.aiddata.org	1	0	0.028	0.166	1,371
Corruption							
	Government Officials	BenYishay et al. 2017 http://geo.aiddata.org http://www.afrobarometer.org	3	0	1.561	0.461	1,371
	Police	BenYishay et al. 2017 http://geo.aiddata.org http://www.afrobarometer.org	3	0	1.837	0.540	1,371
	Judges	BenYishay et al. 2017 http://geo.aiddata.org http://www.afrobarometer.org	3	0	1.431	0.427	1,371
	Tax Officials	BenYishay et al. 2017 http://geo.aiddata.org http://www.afrobarometer.org	3	0	1.604	0.472	1,215
	MP	BenYishay et al. 2017 http://geo.aiddata.org http://www.afrobarometer.org	3	0	1.473	0.471	1,215
	Permit Bribe	BenYishay et al. 2017 http://geo.aiddata.org http://www.afrobarometer.org	3	0	0.298	0.330	1,371
	Police Bribe	BenYishay et al. 2017 http://geo.aiddata.org http://www.afrobarometer.org	3	0	0.317	0.384	1,371

Without Cash	BenYishay et al. 2017 http://geo.aiddata.org http://www.afrobarometer.org	1	0	0.676	0.268	1,215
Active	www.aiddata.org	1	0	0.370	0.483	1.371
Inactive	www.aiddata.org	1	0	0.139	0.346	1.371
Grid Cell Level at 50km (Model 10)						
FDI	www.fdimarkets.com	1	0	0.131	0.338	18,143
Active	www.aiddata.org	1	0	0.123	0.329	18,143
Inactive	www.aiddata.org	1	0	0.070	0.256	18,143
Urban	www.ifpri.org	1	0	0.061	0.240	18,143
Crop	www.ifpri.org	1	0	0.781	0.413	18,143
Area Water	www.ifpri.org	8449.58	0	81.47	659.47	17,875

Table SA1: World Bank and China Pan-African Results, Lags, and Alternative Controls

VARIABLES	(S1) WB and China	(S2) World Bank	(S3) China	(S4) Aid Lag 1	(S5) Aid Lag 2	(S6) Aid Lag 3	(S7) No Controls	(S8) Expanded Controls
active	-0.179***	0.059***	-0.174***	-0.124*	-0.096	-0.124*	-0.146**	-0.109
	(0.014)	(0.014)	(0.014)	(0.075)	(0.085)	(0.075)	(0.075)	(0.079)
inactive	-0.216***	-0.358***	-0.220***	-0.407***	-0.406***	-0.407***	-0.426***	-0.364***
	(0.018)	(0.018)	(0.018)	(0.073)	(0.073)	(0.073)	(0.072)	(0.081)
Observations	8,756	8,756	8,756	1,371	1,371	1,371	1,374	1,215
R-squared	0.331	0.345	0.331	0.234	0.233	0.234	0.216	0.240
Baseline controls	YES	YES	YES	YES	YES	YES	NO	NO
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Difference in difference	0.037	0.417	0.046	0.283	0.310	0.283	0.279	0.255
F test: active-inactive=0	2.845	351.085	4.300	7.612	7.842	7.612	7.560	5.275
p value	0.092	0.000	0.038	0.006	0.005	0.006	0.006	0.022

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table SA2: Grid Cell Approach

VARIABLES	(S9) 25 km	(S10) 50 km	(S11) Inhabited Cells Only 50km
active	-0.016***	-0.055***	-0.065***
	(0.005)	(0.006)	(0.007)
inactive	-0.088***	-0.214***	-0.234***
	(0.007)	(0.011)	(0.012)
Observations	17,902	17,875	14,208
R-squared	0.066	0.211	0.210
Baseline controls	YES	YES	YES
Year FE	YES	YES	YES
Country FE	YES	YES	YES
Difference in difference	0.071	0.159	0.168
F test: active-inactive=0	89.150	164.160	146.227
p value	0.000	0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure SA1: Moran's I spatial correlogram

Residuals

Distance bands	I	E(I)	sd(I)	z	p-value*
(1-2]	0.000	-0.001	0.005	0.238	0.406
(1-3]	0.002	-0.001	0.003	0.753	0.226
(1-4]	-0.023	-0.001	0.003	-8.161	0.000
(1-5]	-0.024	-0.001	0.002	-9.855	0.000

***1-tail test**

Table SA3: Spatial Autoregressive and Spatial Error Models

VARIABLES	(S12) Spatial Lag	(S14) Spatial Error
active	-0.178**	-0.184**
	(0.083)	(0.086)
inactive	-0.430***	-0.427***
	(0.074)	(0.075)
Observations	1,371	1,371
Baseline controls	YES	YES
Year FE	YES	YES
Country FE	YES	YES
p value rho/lambda	0.908	0.768
Difference in difference	0.252	0.243
Chi2 test: active-inactive=0	5.303	4.534
p value Chi2	0.021	0.033

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1