Winning Hearts and Minds or Stoking Resentment? Exploring the Effects of Chinese Foreign Aid on Africans' Perceptions of China

Evan A. Jones*

Dept. of Government and Politics,
University of Maryland, College Park

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Abstract

As China expands its worldwide economic footprint through ambitious policies such as the Belt and Road Initiative, an increasing number of average people are exposed to Chinese workers and China's business practices. These experiences in turn shape their perceptions of China. One facet of China's foreign economic activities at the center of scholarly and policy debates is foreign aid. While IPE and China scholars have focused on the economic effects of China's official financing, no studies examine how aid shapes citizen's opinions of China in recipient countries. I propose a two-part mechanism through which aid influences perceptions—exposure and filter pathways—and predict that China's financing has differential effects by type. Direct exposure to Chinese aid fosters resentments toward China when the project has mixed development and commercial purposes. Other forms of aid have inconsistent effects. However, aid primarily operates via the filter pathway. As Chinese aid becomes more salient within a country, citizens associate Chinese influence with their own government. Citizens then use their satisfaction with the ruling regime, or lack thereof, as a heuristic for how they feel about China.

*eajones3@umd.edu

Since China launched its Going Out Policy in 1999, its foreign economic footprint has grown dramatically. Apart from expanding its foreign direct investment portfolio, foreign aid has also been a key element of China's global strategy. African countries were some of the earliest beneficiaries of China's Going Out Policy and continue to be major recipients of Chinese aid. Between 2000 and 2012, China committed roughly 52 billion dollars (deflated 2014) in foreign aid to African countries (Bluhm et al. 2018).[1] More recently at the 2018 Forum on China-Africa Cooperation, Chinese President Xi Jinping pledged another $60 billion in unconditional aid and investment to African countries.[2]

Commitments of this magnitude have made China an increasingly important player in global aid and finance. Yet, its aid practices do not strictly adhere to the norms of the Organization of Economic Cooperation and Development (OECD). Strange et al. (2017) classify Chinese official finance into two categories: concessional and non-concessional. While the former aims to advance China's foreign policy aims, the latter advances more parochial commercial interests (Dreher et al. 2018). This non-traditional approach to aid has drawn criticism from scholars and Western policy-makers who have labeled China a 'rogue donor' (Naím 2007) with less-altruistic or even malign interests (Alden 2005; Tull 2006; Halper 2010).

This is the official narrative advanced by the United States government as well. In its 2017 National Security White Paper, the United States identifies Africa's strategic importance and frames the US role in the region as offering an economic alternative to "China's often extractive economic footprint on the continent." To match word with deed, the US signed into law the *Better Utilization of Investments Leading to Development* (BUILD) Act of 2018, which transformed the Overseas Private Investment Corporation (OPIC) into the US International Development and Finance Corporation. At $60 billion, the new body has double the budget of OPIC. More importantly, it can take an equity stake in its investments, unlike OPIC.

The tit-for-tat competition between these two countries highlights the inherently geopolitical nature of foreign aid and reflects a well-established literature on the foreign aid allocation (Morgenthau 1962; Schraeder, Hook, and Taylor 1998; Alesina and Dollar 2000; Kuziemko and Werker 2006; Bueno de Mesquita and Smith 2007; Berman, Shapiro, and Felter 2011; Vreeland and Dreher 2014; Dreher and Fuchs 2015). However, these forms of economic assistance also play a role in Sino-US soft power competition. Once initiated, projects may have short and long term effects on local communities. Scholars have identified both deleterious and positive effects of Chinese aid and investment such as increased local corruption (Isaksson and Kotzadam 2016; Brazys et al. 2017), environmental degradation (BenYishay et al. 2016), improved economic development (Dreher et al. 2016), and reduced interregional economic inequality (Bluhm et al. 2018). Yet, to the author's knowledge, there is no research that explores how foreign aid impacts individual's opinions of donor countries.

[1] This number reflects only projects that qualify as complete or implemented and ignores commitments which vastly out pace realized projects. For example, if one includes commitments, China's official finance to Africa between these years approaches $121.8 billion (USD deflated).

[2] Fifield, Anna. "China pledges $60 billion in aid and loans to Africa, no 'political conditions attached,'" Washington Post, Sep 3, 2018. Accessed online at `https://www.washingtonpost.com/world/china-pledges-60-billion-in-aid-and-loans-to-africa-no-strings-attached/2018/09/03/a446af2a-af88-11e8-a810-4d6b627c3d5d_story.html?noredirect=on&utm_term=.575c79c3bbd7`.

In this paper, I seek to answer the following questions: (1) What is the effect of foreign aid on individual's attitudes toward donor countries? (2) More generally, does aid and investment win hearts and minds or stoke resentments? (3) What are the mechanisms through which aid influences individual's opinions? (4) Do concessional and non-concessional aid have differential effects? (5) Finally, do other domestic factors or individual characteristics moderate the attitudinal effects of aid? Answers to these questions are pertinent to China scholars and political economists alike.

For China scholars, there is a need for more systematic analysis of the micro-level effects of Chinese aid to better understand if, and how, this relates to debates about 'rising' Anti-Chinese sentiments. Apart from anecdotal evidence and qualitative case studies in Africa (Negi 2008; Hess and Aidoo 2015), we have little theoretical understanding of this process and less empirical evidence from which to draw any conclusions. This paper aims to provide micro-level theoretical foundations upon which we can build a better understanding of why people respond to China's presence in their local communities and economies.

Within political economy, there is a long tradition of survey and experimental work studying the determinants of individuals' attitudes toward a range of economic issues including trade (Scheve and Slaughter 2001; Mayda and Rodrik 2005; Hiscox 2006; Mansfield and Mutz 2009; Kaltenthaler and Miller 2013; Naoi and Kume 2015; Mutz and Kum 2017; Owen and Johnston 2017; Rho and Tomz 2017), foreign direct investment (Pandya 2010), preferential trade agreements (Spilker et al. 2016), and foreign aid (Findley et al. 2017). While these studies identify the role of sectoral, factoral, and sociotropic variables in driving personal opinions and beliefs, they all treat economic issues as the dependent variable. Utilizing economic variables as a treatment is more rare. To my knowledge, this is the first paper to explore how exposure to foreign aid influences individual's attitudes toward the donor country.

I argue that aid can have differential effects on people's attitudes toward donors depending on the mechanism through which they interact with the aid. I propose two pathways. The first is a direct path, which I call the *exposure pathway*. This applies to citizens living near projects who are likely to be directly exposed to aid projects and their outcomes, good or bad. For example, individuals may benefit from training or educational programs, new hospitals, schools, or infrastructure. Conversely, they may experience increased environmental degradation and local corruption. The second path, which I call the *filter pathway*, is indirect. As donor lending to a recipient country increases, there is increasing likelihood it will become politicized and become a focal point of public debates. Thus, even individuals who may not be directly exposed to aid projects are likely to form opinions on the issue. These people filter the information they receive about aid and donors through prior political beliefs and feelings toward the government. Whereas exposure effects are conditional on the aid type itself, filter effects are conditional on peoples' partisan attitudes, national political discourse, and the political environmental factors more generally.

To test these mechanisms, I utilize geo-coded Afrobarometer survey data from 2014-2015 (BenYishay et al. 2017) that asks respondents multiple questions about Chinese influence in their country and geo-coded data on Chinese government-financed projects in Africa over period from 2000-2014 (Bluhm et al. 2018). By matching respondents with project information, I identify those who experience aid primarily via the exposure pathway versus those who experience aid through the perception pathway.

The preliminary findings suggest strong and consistent support for the filter pathway. People's attitudes toward China are strongly correlated with whether they are satisfied with their current government, even after controlling for direct exposure to Chinese-funded projects. Pro-government individuals are more positively assess Chinese influence in their country whereas dissatisfied individuals see China's involvement negatively. The effect of direct exposure is smaller and negative, but is inconsistent and only significant when the geographic window used to match people and projects is constrained to 10 kilometers.

However, my initial analysis is limited in two ways. First, it homogenizes across all projects types, eliminating the possibility for exploring conditional effects of exposure. Second, while government satisfaction is a robust predictor of attitudes toward China, it is unclear the degree to which Chinese aid influences these attitudes, if at all. The next version of the paper intends to address the first shortcoming by building a bipartite network model of respondents and projects that incorporates a broader range of project-specific information such as flow class, sector type, and investment amounts. To address the second shortcoming, I will gather country-level data on Chinese aid is framed in the context of domestic political debates.

The paper proceeds in a straightforward fashion. In the next section, I present my theory. I then introduce the data and empirical strategy. Afterwards, I present my initial results. Finally, I conclude by discusses the theoretical implications of the findings and outlining the project's future directions.

Theory

I posit two potential pathways through which aid can influence citizen's opinions in recipient countries. The first way is through direct exposure to projects. Assuming aid is not captured by elites, it will manifest at the local level as projects which will have an impact on citizen welfare, for better or worse. Even if people are not the direct beneficiaries of aid, if they are close to an aid-receiving community they may directly witness its effects on those communities or know people from those places. Because of the personalized nature of direct exposure, it should have a strong effect on people's attitudes. As the old adage goes, "seeing is believing."

The second way foreign aid can shape public perceptions of donors is through national political debates. While foreign aid is not a headline-grabbing issue in many developed countries, in aid-dependent countries foreign assistance is not only salient but may be so to the degree of ubiquity.[3] Additionally, even if a country is not aid-dependent, large foreign financing deals such as those China has signed with many developing nations are likely to receive a great deal of media attention and spark public debate. Thus, while individuals may not be directly exposed to aid, they can still 'experience' it after is has been filtered through domestic political discourse.

[3] For example, Findley et al. 2018 describe Ugandan byways lined with signs indicating foreign-funded projects.

It is also important to note that these mechanisms are effect agnostic. Either one could positively or negatively shape public perceptions of donors. Rather, the exposure pathway is contingent on aid-specific factors while the filter pathway depends on individual's prior beliefs and the domestic political climate.

Different Aid Modalities and the Exposure Pathway

To understand how aid influences individual's perceptions of donor countries, I start by unpacking different aid modalities, or the ways in which donor and recipient characteristics and preferences shape aid allocation. There are two competing narratives about foreign aid in the international political economy literature. Each narrative has important implications the ways in which individuals should perceive donor countries. Together they depict a complex theoretical picture.

The first framework treats aid as primarily driven by political prerogatives. Scholars in this vein argue that aid serves as a means for donor countries to advance their foreign policy goals in a politically expedient way (Bueno de Mesquita and Smith 2007, 2009; Qian 2015). In other words, aid is nothing more than a quid pro quo, or 'bribe' (Morgenthau 1962), in which donor countries buy the fealty of recipient country elites. Promoting genuine economic development or democratization is an afterthought. Without stringent oversight, the aid is bound to be co-opted by elites in the recipient country (Bráutigam 2000; Gervasoni 2010; Smith 2008). Once captured, these elites engage in clientelism, doling out rewards to their coalition of supporter and further entrenching their grip on power (Morrison 2009, 2012). This line of reasoning and evidence paints a rather cynical view about the effects aid. Not only does it not promote development or better governance, it actually has deleterious effects on both. However, scholars have shown that not all aid follows these patterns (Alesina and Dollar 2000).

A second framework points to aid effectiveness. Since the Cold War aid has increasingly gone to poor countries, is more targeted, and less prone to elite capture (Bermeo 2010, 2011; Dietrich 2013; Lamoreaux, Michas, and Schultz 2015). By targeting specific issues such as poverty relief, health, and infrastructure, new aid programs are more likely to reach local communities and promote development (Fuchs, Dreher, and Nunnenkamp 2014; Lee and Lim 2014; Bodenstein and Kemmerling 2015). Although aid programs have traditionally been determined via a bargaining process between donors and recipient governments, a significant amount of aid now bypasses the hands of elites altogether. Through cooperating directly with subnational actors such as opposition parties, local health workers, and civil society groups, donor countries and institutions such as the World Bank are more likely to effectively foster economic development, government accountability, and strengthen democracy (Mavrotas and Ouattara 2006; Altincekic and Bearce 2014; Winters and Martines 2015). And even when programs do cooperate with national-level governments, they are more likely to involve conditions that decrease fungibility and discourage clientelism (Birchler, Limpach, and Michaelowa 2016).

These studies make clear that exposure to aid can have complex, and potentially competing, effects on citizen's perceptions depending on factors such as conditionality, the directness of disbursement mechanisms, and program type. Each of which will shape whether aid has positive or negative effects at the micro-level. Where then do Chinese aid practices fall along this spectrum? The empirical evidence suggests China does not fall neatly into ether the politically-motivated or altruistic development category.

As Dreher and co-authors (2018: 131) point out, it is important to distinguish between different types of Chinese lending as China's portfolio of development finance is quite diverse and motivated by foreign policy *and* development priorities. One useful typology that parses out varieties of Chinese financing is AidData's TUFF methodology (Strange et al. 2017). The TUFF typology separates Chinese financing into two main categories depending on whether it meets OECD standards for official development assistance (ODA-like). To qualify as ODA, financing must be provided by official agencies to developing countries or multilateral institutions; promote the economic development and welfare of recipient countries as its main priority; and have a grant component that meets or exceeds 25 percent. If the lending fails to meet these stipulations, but is still funded by a Chinese government agency, then it is considered other official financing (OOF).

China emphasizes the political condition-free nature of its foreign aid (ODA-like) as a key selling point over Western and multilateral donors. In contrast to traditional donors, Chinese official financing follows a 'demand-driven' process (Bräutigam 2011; Kragelund 2011; Reisen and Stijns 2011) whereby recipient governments approach China with specific proposals. China then decides to allocate the money or not. Once a project receives a green light, China's *modus operandi* is to control projects through the implementation phase and use Chinese contractors to conduct work (Bräutigam 2009). After project completion, "local ownership" is the norm (Nissanke and Söderberg 2011: 26).

While the Chinese play an intermediary role in the implementation phase, recipient country elites are in the driver seat at the start and finish, leaving room for elite capture and clientelism to take root. There is some evidence to bear this out. Chinese ODA-like projects are more likely to be situated in the home provinces of national leaders (Dreher et al. 2016) and increase local corruption (Brayzs et al. 2017; Isaksson and Kotsadam 2018). However, these negative effects do not necessarily alter individual's opinions. Blair and Roessler (2018) find that Chinese development finance does not alter people's perceptions of state legitimacy in Africa. Finally, there is evidence that China's ODA-like finance increases economic growth at rates similar to US and OECD aid (Dreher et al. 2017).

While ODA-like financing tends to be allocated towards health, goverenance and education, Chinese OOF projects target specific development needs such as infrastructure, energy creation, mining, and transportation. While this type of 'hard' development is associated with local environmental degradation (BenYishay et al. 2016), it also produces positive results. In Africa, Chinese OOF projects have improved local household welfare (Martorano et al. 2018) and its 'connective financing,' or transportation initiatives, have reduced subnational economic inequalities (Bluhm et al. 2018).

The heterogeneous nature of Chinese development finance suggests it should have differential effects on people's attitudes toward China depending on the type of project they are exposed to. Although each finance type is associated with mixed effects on local communities, I expect that exposure to ODA-like projects will increase the likelihood that people view China negatively. Although evidence suggests it leads to beneficial economic spillovers in local communities, there is also a growing body of evidence showing it increases corruption and that individuals are likely to hold donor countries accountable for this (Findley et al. 2018). Conversely, I expect that exposure to OOF projects will increase the likelihood that people view China positively. OOF has been shown to increase local household welfare and reduce regional income inequality.

Domestic Politics, Prior Beliefs, and the Filter Mechanism

Whereas finance type matters for the exposure mechanism, it is irrelevant in the filter mechanisms. For individuals who have not come in direct contact with Chinese financing, the differences between ODA-like and OOF projects are likely to be semantic, at best. From afar, they both appear as a form of Chinese engagement with the state and the difference between them difficult to discern. The two risk becoming further conflated if politicians, media outlets, and elites in those countries conflate them in their public discourse–a plausible reality.

Because citizens who are not exposed to Chinese projects are less able to identify differences between types and lack personal knowledge from which to render judgments about Chinese aid, they must rely on some heuristic device (Tversky and Kahneman 1974; Gilovich, Griffin, and Kahneman 2002). I argue that domestic politics will serve as the heuristic that informs a person's opinions about Chinese financing and influence in their country more broadly. In recipient countries, aid is a salient issue, especially Chinese development assistance which draws significant media attention. In visits to other countries, Chinese officials often promise large aid and investment outlays, although a good deal of this never materializes (Kurlantzick 2007). Nonetheless, such announcements are prone to stir up domestic conversations.

The tenor of media attention in recipient countries can be quite harsh. Critics complain that Chinese projects exclude local workers by importing their own workers (Bräutigam 2009), degrade local environments, and strip the country of their assets.[4] There is growing anecdotal evidence that criticism of China's lending practices is split along political lines with opposition politicians using it as a rhetorical device to criticize incumbents.[5] Although it is Chinese OOF, and not aid, that lies at the heart of these debates, it unclear whether individuals perceive a difference and if these differences matter.

Goldsmith et al. (2014) argue that for aid to influence opinions it must have staying power within a country and be salient. Dietrich et al. (2018) further indicate that individuals must be able to associated the aid with donor countries. In the absence of attribution, it is not possible for aid to influence peoples perceptions of donor countries. Chinese aid certainly meets both these criterion. Chinese financing and aid are increasingly part of domestic political debates in recipient countries. The 2018 ousting of Sri Lankan Prime Minister Ranil Wickremesinghe and replacement with ex-leader Mahinda Rajapaksa, a staunch ally of Beijing under whom the country's debt to China tripled, highlights the politicized nature of Chinese financing[6]. While this may not be a direct

[4]Fick, Maggie. "Ghana crackdown on illegal gold mining inflames tensions with Beijing." *Financial Times.* April 30, 2017. `https://www.ft.com/content/cb032036-2a63-11e7-bc4b-5528796fe35c`

[5]Crabtree, Justina. "Zimbabwe opposition leader reportedly wants to give Chinese investors the boot." *CNBC.* May 3, 2018. `https://www.cnbc.com/2018/05/03/zimbabwe-opposition-leader-wants-to-give-china-investors-the-boot.html`

[6]Krishan, Francis, and Chrisopher Bodeen. "Rivals China, India cautiously watch Sri

route through which Chinese finance, ODA-like or OOF, influence people's perceptions of China, it is no less important. Indeed, when one considers he rates of people who are directly exposed to Chinese projects versus those whose primary 'exposure' to Chinese financing is via national debates, the latter easily eclipses the former.

Given the politicized nature of public discourse surrounding Chinese financing, I argue that citizen's attitudes will be filtered by the lens of their prior political beliefs. As Findley et al. (2018) discover, citizens' preferences toward aid versus government programs tied to their perceptions of government clientelism and corruption. People who perceive the government as corrupt are more likely to favor foreign aid since it is seen as being controlled by more beneficent actors. Conversely, people who perceive elites as less corrupt prefer government programs. Because of the 'demand-driven' nature of Chinese financing, citizens are more likely to closely associate the recipient government and China than they might with Western aid. Following theories of assimilation and contrast in how individuals place parties in ideological space (Drummond 2011; Lupu 2015, 2016; Busch 2016; Meyer and Strobl 2016), people should then construct their opinions about China based on their feelings toward the current government. As an individual's ideological distance with the government shrinks (more pro-government), the more likely she is to view China positively. Conversely, as the ideological distance grows, the more likely she is to view China negatively.

Data and Empirical Strategy

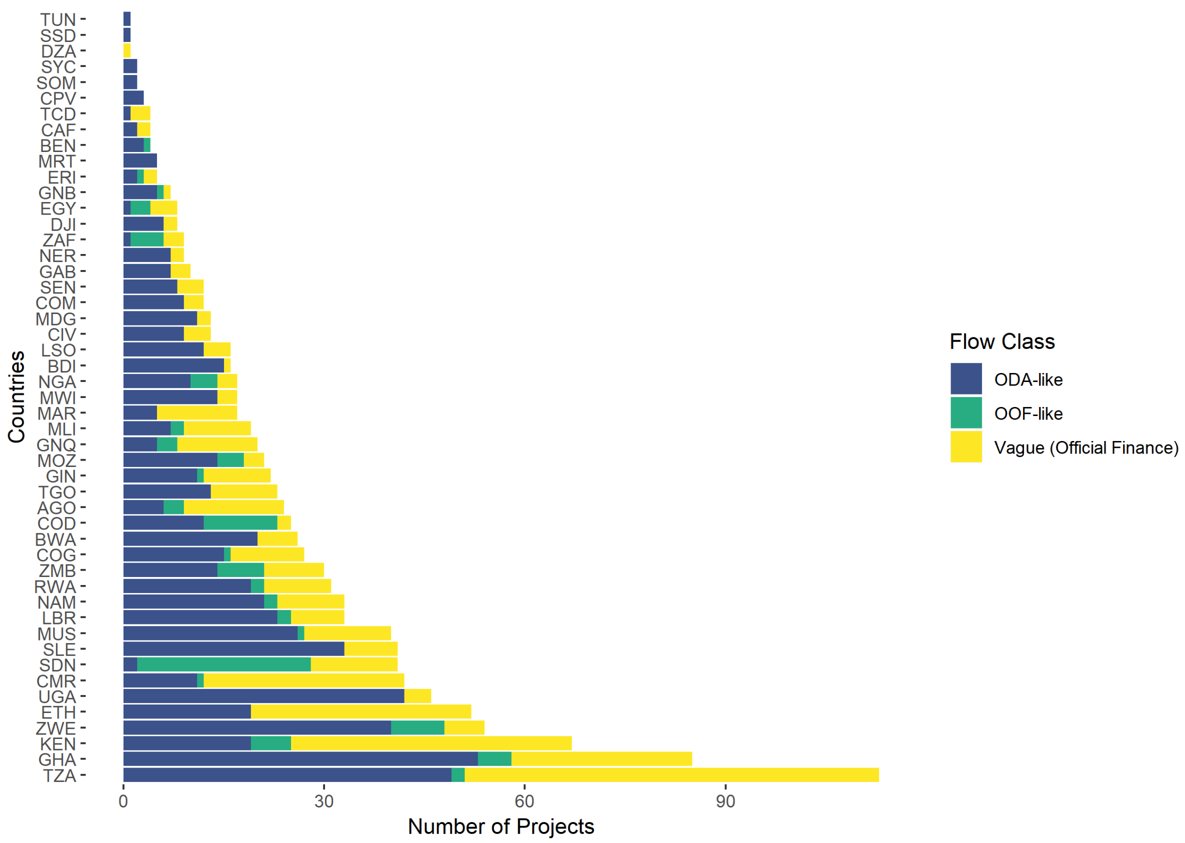
To test my hypotheses, I combine geo-coded Afrobarometer Round 6 survey data from 2014-2015 (BenYishay et al. 2017) with AidData's Geocoded Global Chinese Official Finance Version 1.1.1 dataset (Bluhm et al. 2018) that covers 2000-2012. The round 6 Afrobarometer data surveys respondents from 36 African on a range of social, political, and economic questions, a number of which specifically pertain to people's perceptions of China. A number of the variables below draw on these questions; I denote the associated questions in parentheses where relevant.[7] After dropping Swaziland because the China-related questions are not asked there, my final data includes 38,036 respondents from 35 countries and 7,159 township-villages.

The Chinese finance data includes project level information on 1650 projects in Africa totaling 128 billion USD (deflated 2014). To ensure the geographic precision of the data and that respondents are likely to have been 'exposed' to a project, I follow the conventional approach in the literature (Knutsen et al. 2017; Brazys et al. 2016; Isaksson and Kotsadam 2018) and only include projects coded at precision levels 1 or 2. This ensures the associated latitude and longitude either exactly correspond to the geographic location of the project or within 25 km (Strandow et al. 2011). Figure 1 plots the distribution of the remaining 1183 projects by country and flow class over the period 2000-2012. The vast majority of financing projects fall into either the ODA-like category (composing roughly 50% of projects or more in most countries) or Vague (Official Finance). The latter category is an umbrella that captures ODA-like and OOF-like projects but for which there is insufficient information to make a distinction; in other

Lankan crisis." *Sydney Morning Herald*, November 6, 2018. `https://www.smh.com.au/world/asia/rivals-china-india-cautiously-watch-sri-lankan-crisis-20181106-p50eaz.html`

[7] The wordings of each question I use are located in appendix A

Figure 1: Chinese Aid Projects by Recipient Country and Flow Class



words, there may be 'mixed' development and commercial intent (Strange et al. 2017).

While the geographical and temporal limitations the data may omit important variations in the effect of aid on individual perceptions over time and inhibits my ability to generalize beyond Africa, the empirical and theoretical advantage of using geo-coded data outweighs these shortcomings. Ecological inference is a key obstacle facing studies which try to measure the treatment effect of variables like foreign direct investment or foreign aid on individual attitudes, but cannot identify respondents who have directly received treatment versus those who have not. Under these conditions, researchers must aggregate individuals to a higher level of analysis and make a strong assumption that treatment or exposure to these variables is homogeneous. As a result, we are limited in the type of theoretical arguments we can make. Using geo-referenced data allows me to overcome these issues and test my mirco-level theoretical mechanisms.

Measuring Opinions of China

One advantage to the Afrobarometer survey data is that it asks multiple questions about people's views of China's activities in their country. I utilize question 81B to measure individual's opinions of Chinese influence in their country which asks: "Now let's talk about the role that China plays in our country. In general, do you think that China's economic and political influence on [ENTER COUNTRY] is mostly positive, or mostly negative, or haven't you heard enough to say"? Potential responses include a 5 point Likert scale as well as a "Don't know/Haven't heard enough" and "Refused to answer" category. I drop observations that refused to answer or claimed not to know enough.

Although this question does not ask people about their general opinion of China as a country and invokes a domestic frame by asking about China's role *in* the recipient's country, it is the only question that asks about both aspects of China's involvement in people's countries and makes no assumption about people's prior opinions.[8] The distribution of responses is overwhelmingly biased towards positive opinions: 7.3 percent of respondents say "Very negative," 10.3 percent say "Somewhat negative," 8.4 are indifferent, 42.1 percent say "Somewhat positive," and 31.9 percent say "Very positive." While these numbers may represent a notable crest in China's standing on the African continent which have since regressed to lower levels, they nonetheless exhibit China's success in cultivating a positive image via its financing instruments. When asked about the reason for China's positive image in their country, the largest plurality of respondents reference its investment in infrastructure and development. Coupled together, these descriptive statistics imply the data may be biased toward finding a positive effect on the aid variables.

Measuring Foreign Aid: Exposure and Filter

To measure aid and test my two proposed causal mechanisms, I create multiple proxies for each mechanism. For the exposure pathway, I match individuals to project locations based on their geographic coordinates. Any individual within 25 km of a project receives a 1 for `exposure` and 0 otherwise.[9] To account for potentially heterogeneous effects across aid types, I split the exposure variable into `ODA exposure` and `OOF exposure` which are separate binary variables for each type of project. I also create a third category, `Vague exposure`, which measures peoples exposure to projects for which there is insufficient evidence to determine whether it qualifies as ODA-like or OOF. Therefore, the category contains projects of both types and serves as a quality control variable. Since I expect ODA and OOF projects to have opposite effects, then they should negate each other in the vague variable, resulting in null effects. If not, this poses a challenge to the veracity of the exposure variables.

Controls, Matching, and Model

Based on the extant literature, there are a number of alternative factors that could shape individual's attitudes toward China. The IPE literature on attitudes toward trade, FDI, and migration (Scheve and Slaughter 2001; Mayda and Rodrik 2006; Hainmueller and Hiscox 2010; Pandya 2010; Kaltenthaler and Miller 2013; Owen and Johnston 2017) commonly employ some measures individual's personal economic well-being such as employment, wealth, local economic conditions, asset ownership. Ideally, these should be controlled for as potential confounding factors; however, the observational nature of the data imposes a number of limitations on feasible designs. Namely, the aid projects all precede the survey and so–if we imagine this in experimental logic–a majority of desired

[8] For example, questions 81C and D ask about the main factors that contribute to China's positive or negative image in their country, respectively.

[9] For use in robustness checks, I also calculate all of the exposure-related variables for larger windows such as 10, 15, and 50 km.

control questions are *post-treatment.* Controlling for them may introduce post-treatment bias into the results (King and Zeng 2007). For example, if aid projects increase local educational outcomes, improve household welfare, alter local employment dynamics, or degrade the environment, and people's views of China are influenced by these outcomes, then controlling for such questions post hoc would break causal mechanism chain and bias the effects of aid downward.

In an ideal world, one would have full experimental control over who received what type of aid from China, randomize treatment assignment, and then take pre- and post-treatment measures of people's opinions of China. Unfortunately, this is not possible and it is not safe to assume that pre-treatment control covariates are balanced between those who have and have not been exposed to Chinese aid. For instance, African leaders are more likely to funnel aid projects to their home regions (Dreher et al. 2016), potentially to stabilize support coalitions. As a result, there are theoretical reasons to believe there are potential material and ideational differences between these groups. One commonly employed statistical solution is propensity score matching or re-weighting (Rubin 1973; Imai and van Dyk 2004; Ho et al. 2007) whereby the research estimates an individual's likelihood of receiving treatment (aid project exposure) based on a vector of pre-treatment covariates and then uses the inverse probability to create within-group weights. Afterwards, one can non-parametrically prune the dataset (matching) to induce balance or use weighted generalized linear models (weighting) to account for imbalances during estimation.

Following recent advances in estimating propensity scores for multiple treatment types (McCaffrey et al. 2013; Imai and Ratkovic 2014; Ridgeway et al. 2017), I utilize a gradient boosting model to estimate within-treatment group propensity scores for each observation and then re-weight the final regression (including survey weights). I use four covariates to estimate the propensity for receiving treatment: residence in the home region of one of the country's leaders between 2000-2012, urban residency (urbrur), age (Q1), and gender (Q101).

Although an individual's residency in a home region or urban center could change over the course of the data, and so violate pre-treatment qualifications, I assume this type of movement to be less fluid or 'sluggish.' Moreover, as long as people with preconceived attitudes about China do not systematically migrate to Chinese aid project locations, potential violations of pre-treatment assumptions should not matter. While age has no immediate theoretical impact on attitudes toward China, it is slightly negatively correlated with education (-0.22), suggesting younger Africans are more educated– an important measure of factor endowment and cosmopolitanism in the IPE literature. Additionally, the 2016 United Nations Economic Commission for Africa *Demographic Profile of African Countries* report indicates younger Africans have greater economic and social mobility opportunities than previous generations which should moderate how they feel about Chinese influence. If some individuals are more optimistic (pessimistic) about their economic opportunities, then they may be pre-disposed to see Chinese aid and investment in a positive (negative) light. Finally, gender is a consistently significant control variable in the IPE trade and FDI literature, with women systematically holding different preferences than men. Although this difference is rarely theorized about, it is necessary to account for. Appendix B contains a detailed information on the matching technique. The re-weighted dataset achieves near perfect balance.

Table 1: Exposure Effects of Aid on Attitudes toward China

Variables	Estimate	SE	t-statistic	P-Value
Aid Type:				
ODA	0.028	0.039	0.727	0.468
OOF	-0.314^{*}	0.143	-2.190	0.028
Vague	-0.092	0.061	-1.504	0.133
Controls:				
Urban	0.150^{*}	0.071	2.100	0.036
Age	-0.001	0.003	-0.264	0.792
Female	-0.034	0.043	-0.791	0.429
Home Region	0.431^{***}	0.100	4.306	0.000

$^{*} < .05$; $^{**} < .01$; $^{***} < .001$

Normally, it is sufficient to run a re-weighted difference-of-means test on the dependent variable after achieving balance between control and treatment groups. However, the dependent variable (DV) is ordinal with five levels. I therefore estimate a re-weighted ordinal logit. This offers additional robustness and allows me to simulate changes in predicted probabilities by treatment type. Afrobarometer uses a clustered random sampling approach with each village accounting for an average of 8 respondents. To alleviate the possibility of dependence within these units, I cluster the standard errors by township-village.

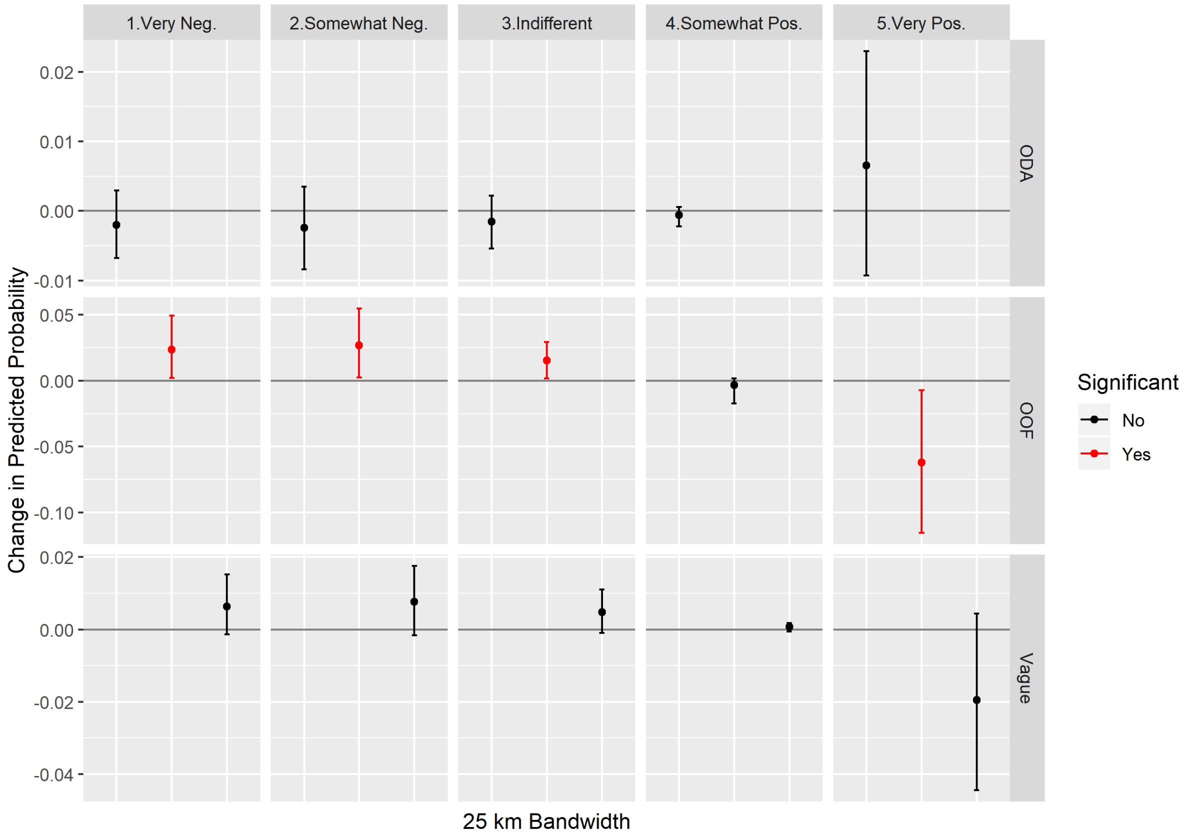
Results

The results provide indicate some viability for the exposure mechanism. There are differential affects across different aid types in line with my expectations, but the direction of the effects are counter to my expectations. ODA exhibits a positive effect on people's attitudes toward China while OOF exhibits a negative effect. However, only OOF achieves statistical significance. Taken together, the somewhat weak findings for the exposure mechanism suggest that aid may be primarily operating through the filter mechanism. I will test this mechanism in the next stage of the project.

Exposure Pathway

Table 1 shows the results from the ordinal logit model. ODA exhibits a very weak, yet positive effect on perceptions of China but the effect is statistically indistinguishable from zero. This is telling, especially since the effective sample size for those who were exposed to ODA is the largest out of all aid types. Exposure ODA alone is insufficient to influence people's attitudes toward China. However, it is not possible to rule out the potential for heterogeneous sub-group effects from the specified model. OOF shows a moderately strong, negative effect on people's perceptions toward China. Moreover, the result is statistically significant. Thus, it appears that although OOF may produce positive economic outcomes for local communities, its detrimental effect on the natural environment appears to outweigh these in the minds of citizens. As expected, the vague category has a small and insignificant effect.

Figure 2: Predicted Probability of Opinion toward Chinese Influence by Aid Type



To aid in analyses, I simulate each aid type's effect on an individual's predicted probability of holding a given perception of China (i.e. at each level of the likert scale). Figure 2 shows the difference in predicted probability between a given aid type and the control group of no exposure. All aid types are shown for transparency even though only OOF is significant. Notably, OOF exposure reduces the probability that an individual will view Chinese influence 'very positively' by about 6 percent. However, it does not drastically increase the probability of viewing China negatively. For instance, the change in probability in the 'somewhat negative' category is only an increase of 2.5 percent. The effect is slightly less for 'very negative' and 'indifferent.' This may be a function of the data. it is heavily toward positive attitudes and so the largest effects are seen in these categories. Extrapolating effects at lower response levels is statistically difficult due to a sparsity of data and theoretically problematic because common support across aid types is more likely to deteriorate and generate model dependence (King and Zeng 2007).

These effects, particularly at the 'very positive' level, are substantively meaningful when we consider that the aid variable is only capturing mere exposure to Chinese aid. These 'treatments' do not isolate the effects of more theoretically important interactions between individual's ideational and material endowments, both of which drive the IPE literature on perceptions toward international economic flows. Given that the independent variables primarily capture geographic exposure, it is not surprising that only OOF exhibits a statistically and substantively noticeable effect. The positive effects of ODA—and likely OOF too—are not necessarily geographically targeted whereas the negative effects of OOF such as environmental degradation are bound to be more visible in a geographic sense.

Moving to the controls, we can see that even after inducing balance on these covariates some of them still noticeable effects. For example, urbanites are more likely to view Chinese influence positively. One plausible explanation for this is that living in a city is a proxy for other characteristics such as higher levels of education or a more cosmopolitan view of the world and this makes people more inclined to see the benefits of Chinese aid. Another possibility is the geographic distribution of aid types. Positively-received Chinese infrastructure and communications projects tend to be clustered in urban areas while more environmentally-damaging and contentious projects such as mining operations are located outside urban centers.

The other substantial effect is for leader home region which concords with the theory advanced by Dreher et al. (2016) that African leaders direct more African aid projects to their birth region whether to bolster support or simply out of favoritism. Unsurprisingly, then, individuals in these regions view Chinese influence more positively as they are more likely to reap the economic benefits of Chinese aid. And if this form of aid redistribution reflects deeper forms of clientelism and not just favoritism, then these individuals might not only be receiving more aid but also projects with more beneficial effects. More probing is needed to identify the mechanism driving the effect for both control variables.

Conclusion

How does aid influence people's perceptions of donor countries? In this paper, I advance a bifurcated theoretical mechanism whereby aid can influence people either through direct exposure or indirectly after being filtered through the domestic political environment. I test the theory by combining Afrobarometer survey data with information on over 1600 Chinese aid projects in Africa. The preliminary results provide some evidence that direct exposure matters, but only in a negative fashion. In particular, exposure other official flows—aid that mixes commercial and development intent—decreases the likelihood an individual will view Chinese influence in their country positively, counter to my expectations. Conversely, China's OECD-like aid had no meaningful effect on attitudes. The mixed findings on the direct exposure mechanism suggest that the primary effect of aid likely operates through the filter pathway.

The next steps of the project entail: (1) testing for more theoretically-meaningful interactions between people's ideational and material endowments and aid project characteristics; and (2) devising a means to test the filter mechanism.

Currently, I homogenize aid flow classes, treating projects within each class as though they should have identical effects on people's attitudes. Such an assumption is problematic. Not only do projects within each class vary in characteristics such as sector type, funding amount, and implementing agency, but their effects likely differ in magnitude and direction depending on an exposed individual's given needs. A poor, young individual stands to benefit more from educational aid than a well-off older individual. Relying on geographic proximity alone cannot account for these potential sub-group effects. One option is to utilize a bipartite network of individuals and projects and weight their edges according to the distance between them. This allows for the inclusion of more covariates, but the question of non-random exposure remains. A potential solution to non-random exposure, i.e. network connections, is to combine propensity score weighting with the graphical structure.

To test for the filter mechanism, I intend to gather news coverage of Chinese aid in all 31 African countries in the data set from 2000-2013. I can then read and identify articles that depict Chinese aid in a way that is politicized along a salient social or political cleavage within countries. Then I can create a country-level measure of national politicization of Chinese aid in each country and explore how correlated this is with overall levels of Chinese aid received by the country. Finally, this will allow me to explore how individual's prior political beliefs interact with the degree of aid politicization to shape their perceptions of Chinese influence.

Appendix A Question Wording

Dependent Variable

Q81B: Now let's talk about the role that China plays in our country. In general, do you think that China's economic and political influence on [ENTER COUNTRY] is most positive, or mostly negative, or haven't you head enough to say?

Controls

Q1: How old are you?

Q101: Respondent's gender (Answered by interviewer)

URBRUR: Urban or rural sampling unit (Answered by interviewer)

Appendix B Matching Approach

The averages of observed outcomes among individuals who receive a treatment may be biased if there are systematic differences between those who do and do not receive the treatment in terms of their potential outcomes (Rosenbaum and Rubin 1983). The ideal way to alleviate imbalances is to randomize treatment assignment; however, in non-experimental settings this is intractable. Matching offers a means of either re-weighting or pruning observable data so as to induce balance on potential confounding variables and thus reduce bias in the estimated effects of a treatment variable (usually binary). I utilize re-weighting to correct for potential imbalances in the data and adjust the approach to account for the multiple treatments (ODA, OOF, Vague).

In this paper, I am interested in estimating the average treatment effect (ATE), or the effect of receiving a given treatment had the *entire* population been observed under that treatment versus another treatment. One can use the inverse probability of treatment weighting (IPTW) (Robins et al. 2000) to estimate the mean μ_t for each value of the treatment t and use these to obtain the unbiased estimates for the treatment effects. I estimate the pairwise ATEs by calculating the following weighted means for each treatment:

$$\hat{\mu}_t = \frac{\sum_{i=1}^{n} T_i[t] Y_i w_i[t]}{\sum_{i=1}^{n} T_i[t] w_i[t]}$$

and the weights:

$$w_i[t] = \frac{1}{p_t(\mathbf{X}_i)}$$

where i are observations, t denote each treatment type, Y is the outcome variable, and $p_t(\mathbf{X})$ is the *propensity score*, or probability that an individual receives the treatment, given their pretreatment covariates $\mathbf{X}$.

Logistic regression is commonly used to estimate propensity scores. For multiple treatments multinomial logistic regression is employed. However, there is a growing literature on machine learning models–particularly, gradient boosting machines (GBM)–as plausible, or even superior, alternatives under certain circumstances (McCaffrey et al. 2004; Lee et al. 2010; McCaffrey et al. 2013). Even under conditions where logistic regression performs sufficiently well, simulations show that GBMs offer smaller variance and thus more precise estimates. To re-weight the data, I estimated propensity scores using both multinomial logistic regression and multiclass GBM, compared their performance, and ultimately utilized the GBM-estimated weights.[10]

An important element of machine learning models is hyperparameter tuning, or optimizing the parameters of the model–such as number of iterations, weight on the penalty term, max number of interactions, etc.–to obtain the best predictive performance on a validation set. Usually, the aim is to balance better predictive performance against *overfitting*, or over-training the model to the idiosyncrasies of the test data and not the true data-generating process. However, overfitting is not a concern for propensity score estimation. As Ho et al. (2007: 219) note, the aim of propensity scores is to provide the best possible predictions, and thus balance, within a given dataset. Respecifying and tuning the models until they give us the best fit does not raise alarm because we seek the best in-sample prediction as opposed to robust out-of-sample predictions. Therefore, from the machine learning perspective, hyperparameter tuning is not as crucial for propensity score estimation as long as the final treatment predictions perform sufficiently well in-sample.

Nonetheless, I fit multiple GBMs, ultimately settling on one with the following hyperparameters:

1. Number of trees = 5000
2. Interaction Depth = 2
3. Penalty weight (shrinkage) = 0.01
4. Maximum number of iterations for optimization = 1000
5. Stop method = Mean standardized effect size
6. Sample weight = Afrobarometer survey weights

Number of trees is the number of decision trees to fit.[11] Interaction depth denotes the highest level of variable interactions allowed. Penalty weight is the reduction in the learning rate (step-size); higher values induce slower learning. Maximum number of iterations refers to the second-stage weight optimization. Stop method is the objective parameter for which the algorithm is trying to minimize loss. Finally, sample weight allows the optional use of prior sampling weights.

Table 2 has two panels. Panel A displays the max mean differences across all control covariates and pairwise treatment comparisons pre- and post-balancing for each matching technique. The standard benchmark indicating problematic imbalance is a max mean unadjusted difference greater than 0.2. As panel A's max difference unadjusted columns

[10] All analyses were done using R. The multinomial logistic regression was implemented using the *CBPS* package (Fong et al. 2016). The GBM utilized the *twang* package (Ridgeway et al. 2017).

[11] In prediction settings, 5000 trees is a very large number and would usually produce an extremely over fit model. Yet, the algorithm indicated that more trees could have produced even better balance. However, additional trees induce exponential computational costs and diminishing marginal returns in better performance.

Table 2: Covariates Balance and Effective Sample Size by Matching Technique

Panel A: Covariate Balance

		GBM		*Multinomial Logit*	
	Type	Max.Diff.Un	Max.Diff.Adj	Max.Diff.Un	Max.Diff.Adj
Urban/Rural	Binary	0.362	0.019	0.364	0.055
Age	Contin.	0.099	0.037	0.089	0.102
Female	Binary	0.024	0.009	0.028	0.005
Home Region	Binary	0.186	0.014	0.174	0.032

Panel B: Effective Sample Size

	GBM		*Multinomial Logit*		
Group	Unadjusted	Adjusted	Unadjusted	Adjusted	Adj.Pct.Rmn
Control	20087.103	18377.916	24772	18673.829	0.91/0.75
ODA	8762.227	6275.199	10685	6035.951	0.72/0.56
OOF	456.008	361.107	615	390.642	0.79/0.64
Vague	1576.089	1410.032	1824	1456.462	0.89/0.80

show, the only variable portending serious imbalance is the urban-rural divide. Home region is also somewhat problematic, though not above the 0.2 threshold. Age and gender do not pose an issue, which is not surprising; they are intentionally sampled in a balanced fashion. Max adjusted differences closer to zero indicate better post-weighting balance. The GBM outperforms multinomial logistic regression on every variable except gender, but the difference is minute. Figure 3 visualizes these differences.

Panel B shows the effective sample size (ESS) remaining after reweighting. Ridgeway et al. (2017) define ESS as a measure of the sample size required for a non-weighted sample to achieve precision equal to that of the weighted sample. They use the following formula:

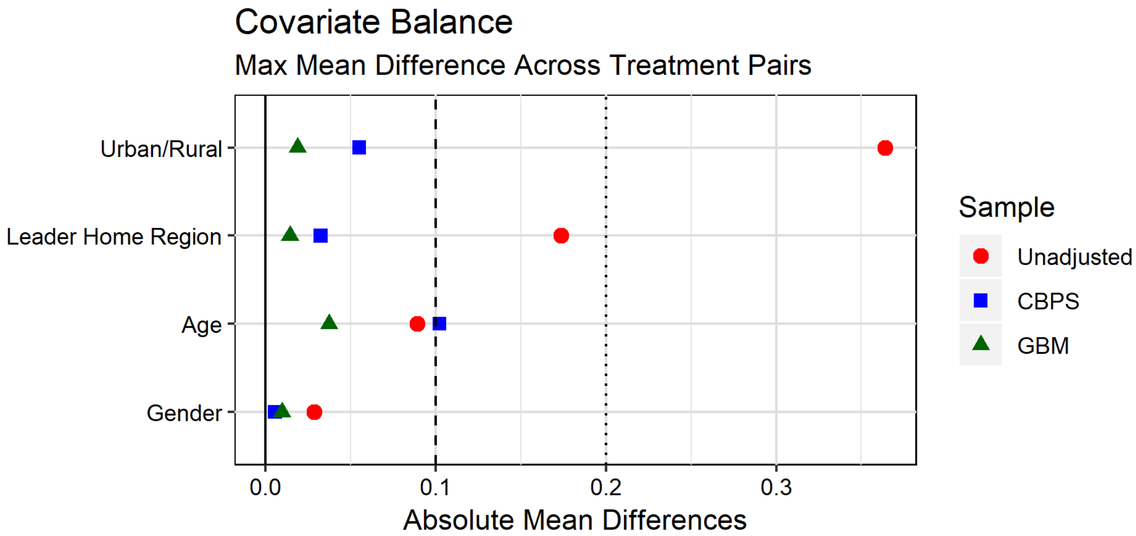
$$ESS = \frac{(\sum_{i=1}^{n} w_i)^2}{\sum_{i=1}^{n} w_i^2}$$

Here, again, GBM beats the multinomial logistic regression as indicated by the percent remaining column.[12] This tells us the percent of observations left after reweighting using each technique. The left value corresponds to the GBM; the right, logistic regression. In all groups, the GBM retains a larger effective sample size post-weighting which translates into smaller standard error when estimating treatment effects.

Figure 4 visualizes the pairwise balance achieved for each pre-treatment covariate using the GBM and multinomial logistic regression. Both methods exhibit satisfactory balance across all pairwise treatment and control comparisons, although the GBM slightly outperforms the logistic regression in balancing OOF vs ODA and Vague vs OOF. The main advantage of the GBM is the number of effective samples it retains. Thus, when

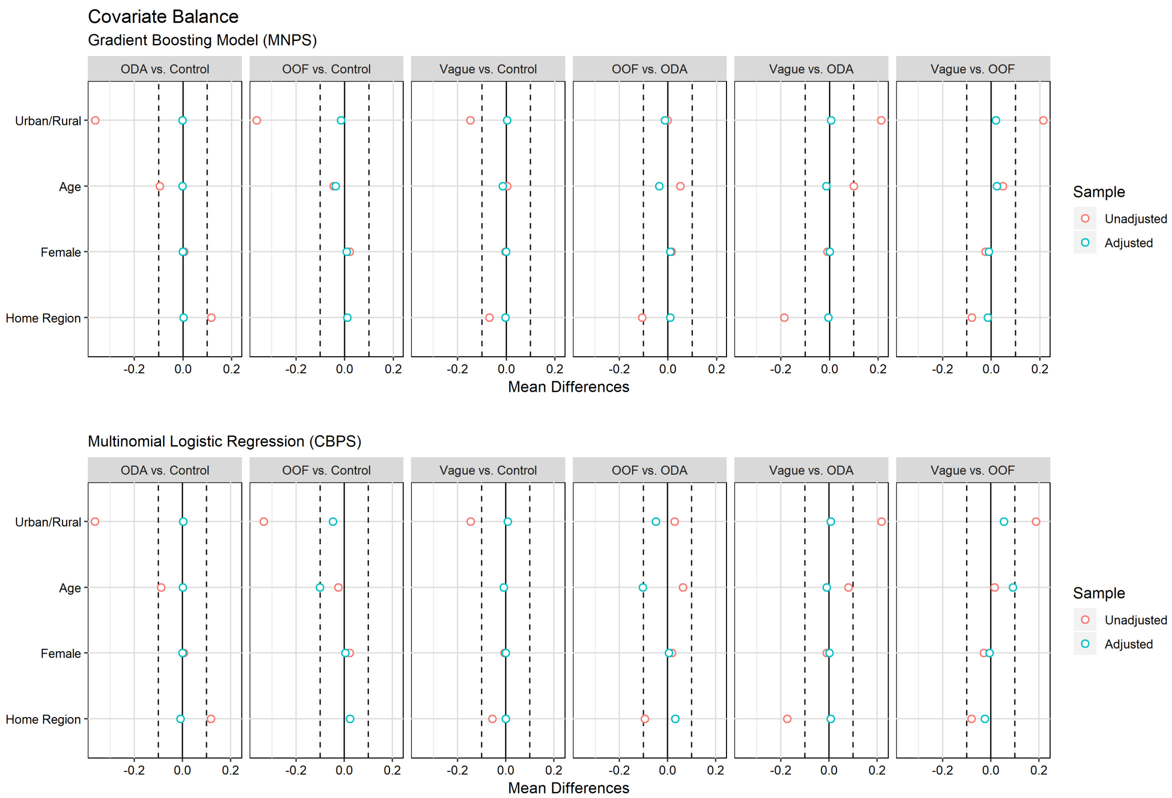
[12] The GBM underestimates the true ESS when estimating propensity scores for the ATE (See Ridgeway et al. 2017) and therefore the unadjusted and adjusted values are not directly interpretable. However, the proportions are accurate and allow for direct comparison.

Figure 3: Post-Weighting Balance by Propensity Score Estimator



fitting the weighted ordinal logit to identify the causal effects of different aid types, the GBM weights provide significantly lower standard errors while the logistic regression introduces intractable levels of variance.

Figure 4: Technique Comparison of Pairwise Covariate Balance



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