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Who Gets the Goodies? Overlapping interests and the Geography of Aid for Trade Allocation in Bangladesh

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Abstract

The Sustainable Development Goal principle of "leaving no one behind" has led to increased attention being paid to patterns of intra-country allocation of foreign aid. We contribute to these efforts by considering a particular type of foreign aid, Aid for Trade (AfT), to discern allocation objectives. We match a novel, geo-coded, dataset on over 11,000 Bangladeshi exporting firms to over one thousand AfT project locations in Bangladesh similarly geo-coded by AidData and expanded by ourselves. We use this data to employ spatial techniques that evaluate political economy logics of allocation, wherein AfT is functionally targeted towards exporting firms, is allocated based on prebendalism, and/or is directed to high poverty areas. Our analysis finds the strongest allocation patterns when all three logics are present. This suggests that allocation logics may not be either/or, but instead, that the subnational locating of aid is driven by multiple aims.

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Introduction

Understanding patterns of subnational aid allocation is important in ensuring that no one is "left behind" as the world strives to achieve the Sustainable Development Goals (SDGs) by 2030. While comparative measures of performance and (in)equality have historically been at the *inter*-state level, understanding *intra*-state (sub-national) development performance is equally important to make certain that no pockets of deprivation are glossed over in aggregate country-level efforts and measures. To this end, a burgeoning literature has emerged examining subnational development inputs and outcomes (Civellia et al. 2018, Kotsadam et al. 2018, Isaksson and Kostadam 2018, Carnegie et al. 2019, Gerhing et al. 2019, Isaksson 2019). With specific regards to aid allocation, recent analyses (Briggs 2017, 2018a, 2018b) have suggested that sub-national distribution patterns may not be pro-poor. Other work has advanced political-economy rationales for what might instead explain sub-national targeting including preference to political leaders' birth regions (Dreher et al. 2016), prebendalism (Bommer et al. 2018), or electoral incentives (Masaki 2018).

This paper adds to these efforts by considering the rationale of sub-national patterns of aid allocation in Bangladesh. Specifically, the paper considers allocation of the so-called "Aid for Trade" (AfT), an aid initiative that stems from discussions in the World Trade Organization's (WTOs) Doha Development Round of trade talks. Broadly, AfT is intended to increase the exporting activity of recipient countries by developing trade-related infrastructure, increasing capacity and compliance with trade-related rules and regulations, and by developing specific export-oriented industries (Brazys and Lightfoot 2016). As of 2019, UNIDO currently classifies some 30% of all official development assistance (ODA), valued at over $30 billion annually, as AfT.[5]

The focus on AfT allows for an exploration if patterns of aid allocation can follow a *functionalist* logic instead of, or in addition to, other prevailing logics of aid allocation. To conduct this analysis, we present a novel, geo-coded, dataset of the population of over 11,000 exporting firms in Bangladesh. This is complemented with an expanded version of AidData's geo-coded aid projects in the country. Bangladesh is an excellent candidate country for this type of study as it has numerous exporting enterprises as well as a reasonable geographic distribution of these firms. These data permit an observation if the firms and projects conform to a functional economic geography explanation of co-location. We are then able to match these observations to other data that could be suggestive of AfT allocation patterns conforming with local need and/or local prebendalism.

[5] https://www.unido.org/events/aid-trade-global-review-2019-supporting-economic-diversification-and-empowerment accessed 29-10-2019

In general, we find support that the geography of AfT allocation coincides with all three logics. That said, we find that the conditional, interactive, effect is much greater than the sum of the parts. While the individual marginal effect of any given component brings a no greater than 10% increase in probability, areas that voted for the ruling party, have high levels of poverty, *and* are home to an exporting firm have a greater than 40% probability of also having an AfT project, ceteris paribus. This is a roughly 166% increase in the base probability of an area having an AfT project of 15%. Collectively, these correlations suggest that it is a combination of logics that drive the allocation of aid projects rather than allocations simply being based on “pro-poor”, “pro-business” or prebendalist interests.

Functional Subnational Aid Allocation

Recently, several studies have investigated the political economy of subnational aid allocation. These investigations have clustered around two distinct political economy logics. The first are investigations into the salience of *prebendalism* in explaining aid allocation patterns. Prebendalism, clientelism and cousinage have long been used as heuristics for understanding the political economy of resource allocation (Lewis 1996, Szeftel 2000, Dunning and Harrison 2010, Brazys et al. 2015). The development of highly-granular, sub-national, data has allowed a fresh look at these issues. These studies have largely found that aid resources are directed to areas that are politically favoured. Both Briggs (2014) and Jablonski (2014) show that aid in Kenya was directed to areas of partisan and ethnic support. Likewise, Dreher et al. (2019) suggest that Chinese aid tends to favour the birth regions of leaders, but show no similar bias for World Bank projects. In contrast, Knutsen and Kotsadam (2020) find that local World Bank aid can increase support for an incumbent, but find no such effect for Chinese aid. An interesting corrective, however, is Masaki (2018) who finds that instead of targeting areas of political support, aid targets areas of with a high proportion of *opposition* in Tanzania. Masaki (2018) argues that this is due to the incumbents’ limited information on the geographic distribution of swing voters, and thus, seeking to sway the preferences of weak opposers.

A second strand of this literature explores the importance of *poverty* or *need* in determining aid allocations. In particular, Briggs’ (2017, 2018a, 2018b) series of investigations, across a handful of countries, finds that foreign aid flows to richer rather than poorer regions, in contrast to the stated aims of the donor actors. Combining these literatures, Brazys et al. (2019) examine if World Bank educational aid in India flows not only to areas of highest educational need, but also to areas with the highest proportion of marginalized individuals in terms of those in scheduled castes and tribes (SC/STs). While finding evidence that this aid does flow to areas of higher need, the paper also finds that flows are highest when the area is represented in government by a SC/ST parliamentarian.

Aid may also be allocated along *functional* lines. While work such as Marty et. al (2017), Lordemus (2019), and Brazys et al. (2019) moves in this direction by assessing if health and education aid flow to areas in greatest need of improvements in those areas, respectively, it is difficult to extract health or education need from general poverty as the latter is likely to be highly correlated with the former. However, by restricting the focus to “Aid for Trade” projects, one can partially strip out the element of personal need as AfT is ostensibly meant to benefit firms, not individuals. While AfT encompasses trade-related infrastructure like transportation links or utilities, it can also be used to classify vocational training programmes or institutional capacity building efforts such as customs or regulatory trainings (Brazys and Lightfoot 2016). In most instances, in order for AfT to be functional, firms need to be sufficiently near to the project locations. AfT that is located to places without exporting firms will have difficulty in fulfilling any sort of functional role.

The political economy logics above rest, to a greater or lesser degree, on assumptions about the degree of “aid capture” or “donor control” (Milner et al. 2016). Donor and recipient countries (and heterogenous interests therein) may often have different preferences over where and how aid is allocated.[6] As Swedlund (2017) argues, reconciling these differences often takes place through an intricate “dance”, wherein each party utilizes the resources at their disposal in an attempt to sway allocation decisions in line with their preferences. Indeed, Rahman and Giessen (2017) use quantitative text analysis to determine informal interests and motivations behind several donors’ forest development projects in Bangladesh. Moreover, as Dionne (2018) demonstrates in discussing the allocation and implementation of AIDS interventions, donor aims may ultimately be frustrated at the local level by authority figures with different preferences or concerns.

In line with Swedlund’s (2017) work, it seems unreasonable to assume that any single allocation preference will crowd out others. In other words, donors’ never have full “control”, nor can aid ever be completely “captured”. Using that recognition, we posit that aid allocations will be largest in areas where diverse interests overlap. While different interests may be more or less effective in different settings, none are likely to be completely ineffectual in any setting. Thus, with respect to our logics above, we would expect that areas that have high degrees of poverty (reflecting donor control), are in important political

[6] Although as implied by Dreher et al. (2019), in some instances, donors may simply not care how aid is allocated.

constituencies (reflecting capture and prebendalist interests), and are home to exporting firms (representing a functionalist logic) will be most likely to also be home to AfT projects.

Case Selection, Data and Methods

Our study focuses on AfT allocation in Bangladesh. Bangladesh is a prime candidate to consider the relationships discussed above as it has a large and geographically disperse population of exporting firms, has a recent history of meaningful political opposition, but also has a large degree of poverty accentuated by intra-country inequality. Recent findings show the existence of 'poverty pockets' throughout the country despite the general reduction in poverty rates over the last decade, which is often attributed to policy bias as well as geographical exclusion (GED 2013; Sen and Ali, 2015; Alam and Iqbal 2016).[7] More recently the country slipped from 143rd to 149th out of 180 countries on Transparency International's Corruption Perceptions Index, suggesting a weak state of governance.[8] A 2014 study focusing on the state of governance in Bangladesh, discusses the confrontational politics and political influence on other institutions affecting democratic governance and service delivery in the country (see SOG 2014). Additionally, although recently graduated, until 2018 Bangladesh had been the most populous of the least developed countries in the world.[9] However, despite this size and importance, Bangladesh remains relatively understudied in terms of the political economy of aid allocation and effectiveness.[10]

In order to look for spatial relationships between AfT and our measures of *functional, prebendalist* and *poverty* allocation logics in Bangladesh, we draw on data from a diverse range of sources. First, as "outcome" data, we utilize AidData's (2016) "Bangladesh Selected Donors" database. This database contains 288 projects at 3,641 unique project locations. The "Aid for Trade" designation has been critiqued as overly broad, with many projects officially classified as such having little, if any, discernible relationship with export activity (Brazys and Lightfoot 2016). Accordingly, we pared the projects by using a textual algorithm that searches project sector names and descriptions for terms indicating the projects are either trade-related infrastructure, trade-related industry development (including technical training), or related to customs or trade procedures. The full search algorithm is available in the appendix. We then manually reviewed the results of this algorithmic sorting, identifying a

[7] Household Income and Expenditure Survey(HIES) 2005 and 2010 rounds data show that large number of subdistricts experienced increase in poverty despite the reduction in poverty rates in respective divisions; ; levels of moderate and extreme poverty have increased in 158 sub-districts in 2005 and 114 sub- districts in 2010(see GED 2013)
[8] https://www.thedailystar.net/opinion/governance/news/bangladesh-descends-corruption-ranking-1694551 accessed 09-12-2019
[9] https://www.unfpa.org/sites/default/files/pub-pdf/LDC_Fact_Sheet.pdf accessed 09-12-2019.
[10] Some important exceptions include Dietrich et al. 2018, Amin and Murshed 2017; Sawada et al. 2018

total of 97 projects at 863 locations. Of these 863 project locations, 779 were coded at precision code “3” or better, equivalent to precision at the administrative 2 unit (district/municipality) or better. We then expanded this AidData resource by searching project records for projects whose projects locations were at “4” or worse. We were able to identify 332 additional project locations for 3 projects, which we geo-coded following the AidData geo-coding methodology.[11] These efforts resulted in a combined total of 1,111 project locations at precision code “3” or better spread across 98 projects. In the robustness checks below we further restrict AfT projects to those at precision code “2” or better, equivalent to 25km precision. A full list of project names is available in the online appendix. The distribution of these projects is represented graphically in Map 1 (countrywide) and Map 2 (Dhaka area).

Our firm data is a novel, geo-coded, dataset of the population of Bangladesh exporting firms.[12] The base data was sourced from the Bangladesh Export Promotion Bureau’s (EPB) directory of exporting firms.[13] We were able to identify 11,124 firms within this directory. To geographically locate these firms, we first relied upon location information within the database. As this was often incomplete, we added geographic information based on other identifying characteristics, such as firm name, whenever possible. For firms located in and around Dhaka, we also took advantage of the fact that telephone exchange prefixes are geographically indicative.[14] Thus, when land-line information was included in the directory we were able accurately identify the neighbourhood in the absence of that information in the directory. We then used Google’s geocoding API to geo-code all 11,124 firms. We used the API to geo-code by two methods. First, we used the API using full firm information, including firm name and all available address information. Second, we used the API using the most precise geographic unit information available in the directory (neighbourhood, city, district, etc.). We then analysed the distance between these two methods of geocoding. The two geocoding returns were within 5km for 7,296 (66%) of all firms, and within 20km for 9,064 (81%) firms. In these instances, we utilized the full information API geocoding as the coordinates. Some 1,393 firms had geocoded locations greater than 400km apart. Checking these cases most often proved that one of the geocoding methods (usually the full information method) had grossly misidentified the firm with coordinates outside of Bangladesh and we used the more clearly plausible result. The remaining 667 firms which

[11] Available at: http://docs.aiddata.org/ad4/files/geocoding-methodology-updated-2017-06.pdf accessed 21-06-2019

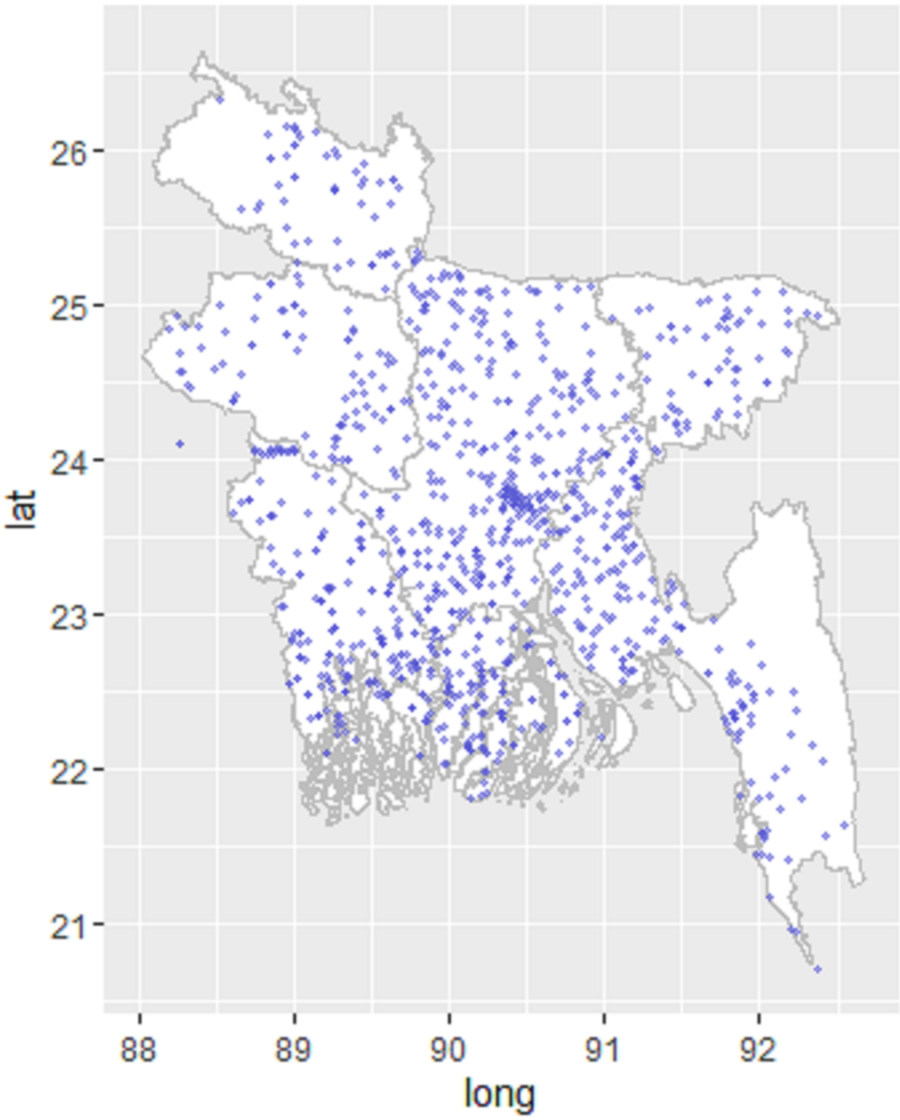
[12] A senior official from the Export Promotion Bureau confirmed in an interview that this directory should substantively capture the entire population of exporting firms in Bangladesh. (Interview date 26-02-2019).

[13] This directory was obtained by directly contacting the Bangladesh Export Promotion Bureau and was provided as a single, 576-page, scanned document on 10-01-2019. Firm names, addresses, and contact information were manually extracted from this scan and inputted into a .csv file.

[14] Where prefixes were identified using http://www.btcl.com.bd/en/200/phoneprefix accessed 02-03-2019.

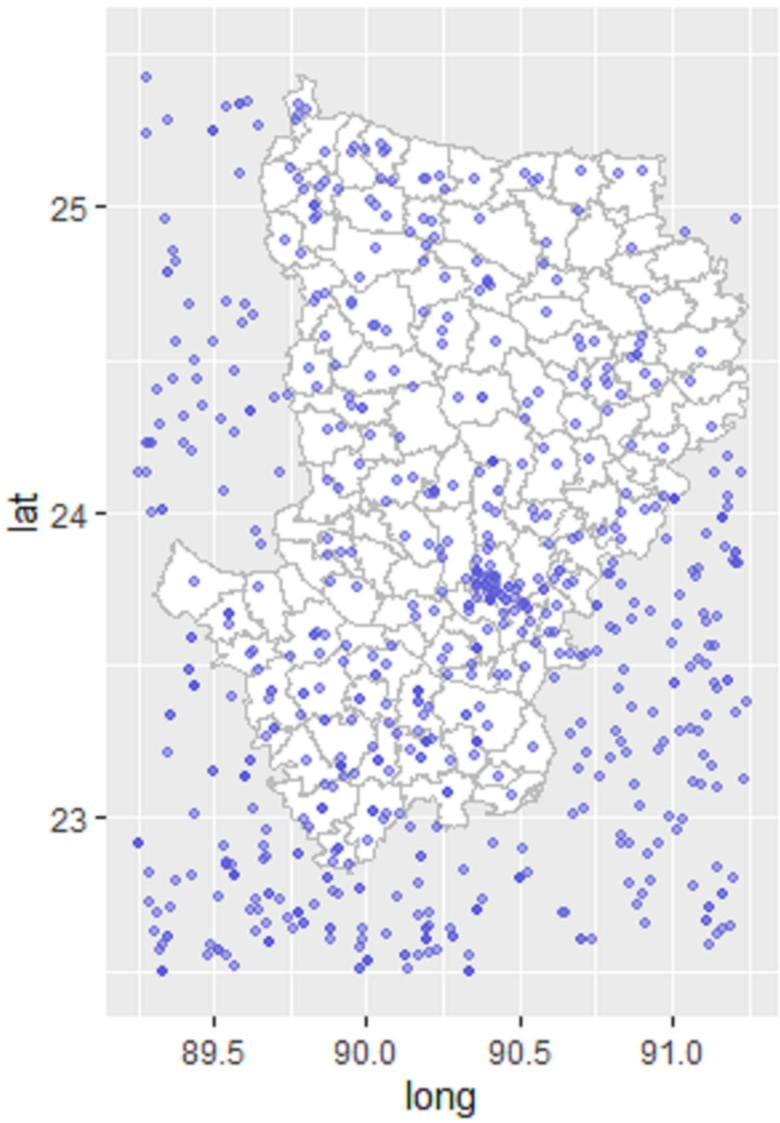
had geocoding discrepancies were hand-checked and in most instances resolved by rectifying a clear spelling error in the firm name or address information. In total, we were able to geo-code 11,115 (99.9%) of the firms.

Map 1: Aid for Trade Locations Countrywide



The exporter directory also contained useful information on the firm sector. Bangladesh's export sector is dominated by apparel-related firms, particularly those in the readymade garment (RMG) industry with 8,297 (75%) of firms in these sectors. Other major industries include software (667 firms), handicrafts (441 firms), and food-related products (523 firms). The geographic distribution of these firms, by sector, is provided in Maps 3 and 4. Circle size reflects the natural log of the number of firms within a given geographic level (neighbourhood, sub-district or district). While the maps indicate clear sectoral and geographic clustering, especially around the two major metropolitan areas of Dhaka and Chittagong, this also shows a reasonable amount of dispersion of firms around the country.

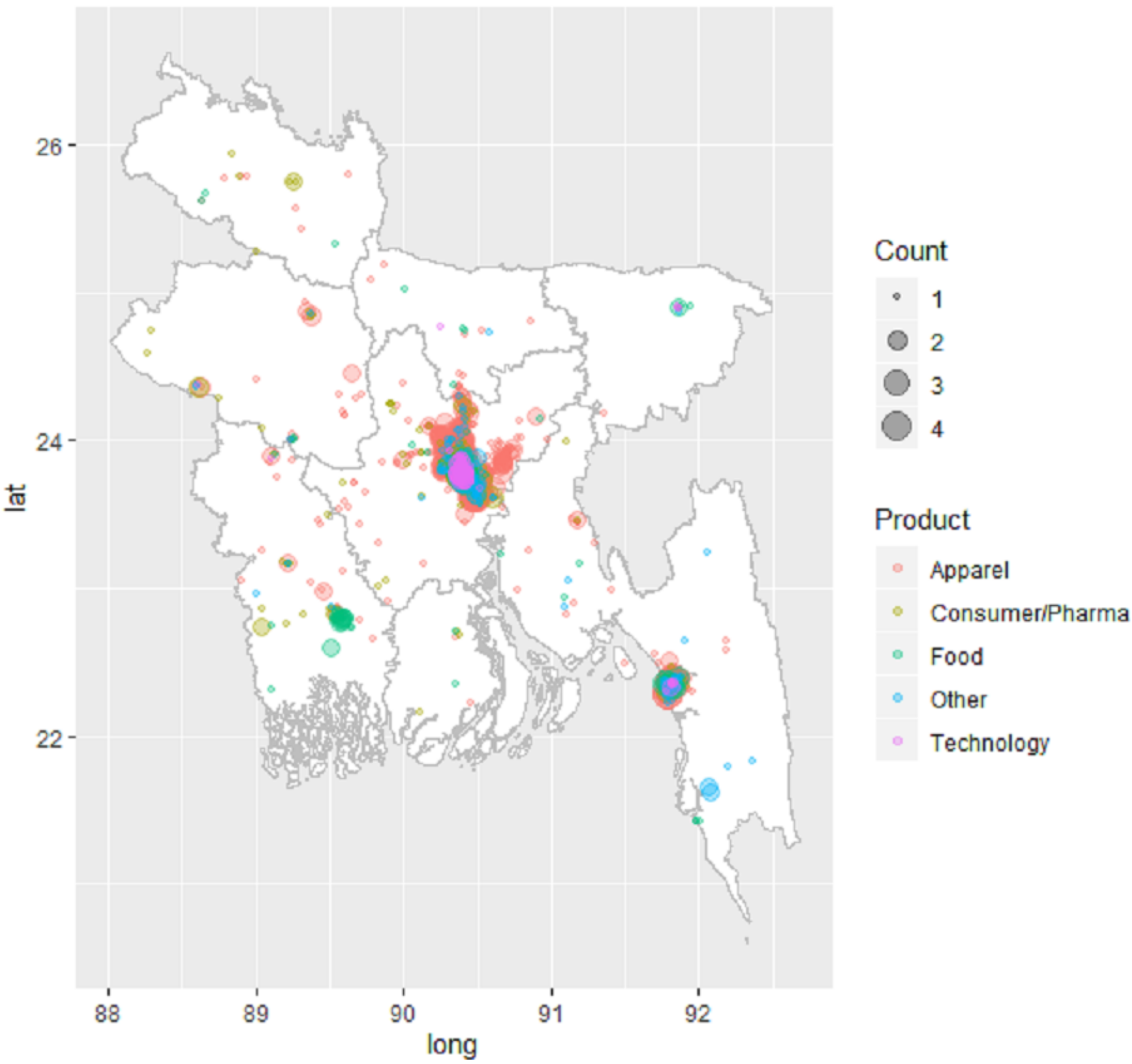
Map 2: Aid for Trade Locations Dhaka Division and Surrounding



In order to observe patterns of allocation, we spatially joined our variables. Our primary analyses utilize 5,160 base geographic areas at the administrative four level (ADM4) (known in Bangladesh as unions). Using polygon shapefiles we determined how many AfT projects or firms are located within the polygon.[15] We find anywhere from 1 to 9 AfT projects in 766 of the 5,160 ADM4 units. For our main analysis, we use this information to create a binary indicator that equals "1" if the ADM4 unit was home to *any* AfT project as our outcome variable. In the extensions below we also utilize the full count of the AfT projects.

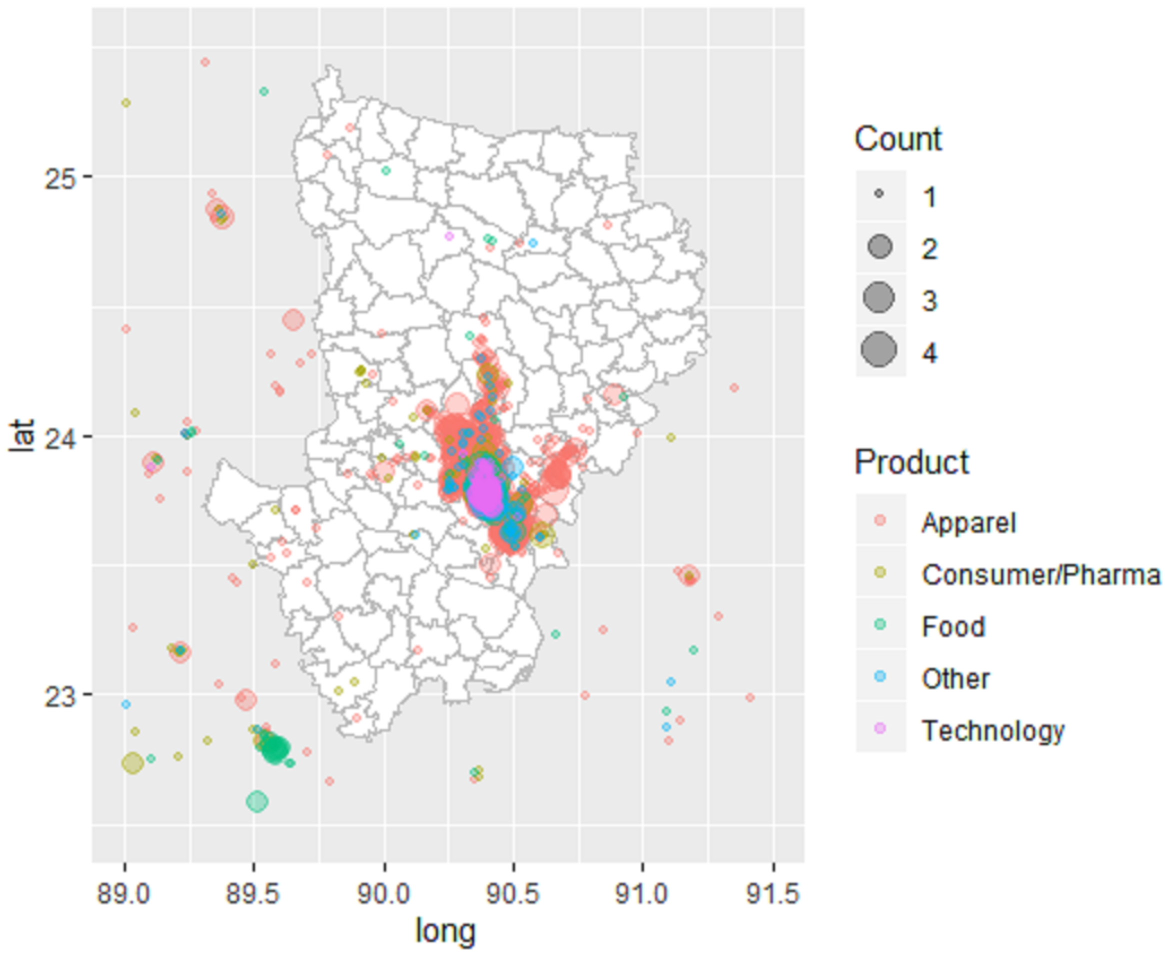
[15] With shapefiles from https://gadm.org/data.html accessed 15-06-2019.

Map 3: Firm Distribution Countrywide



Similarly, our main correlate of interest is a binary indicator, *Exporter,* coded as "1" if an ADM4 unit has *any* exporting firm in its borders. We find from 1 to 415 exporting firms located in 451 of the 5,160 ADM4 units. As a simple cross tab, of the 451 ADM4 units with exporting firms, 112 (24.8%) also have an AfT project location. In contrast, 655 (13.9%) of the 4,710 ADM4 units *without* an exporting firm had an AfT project location. In the model extensions, we also use an *Exporter Count* indicator, utilizing the natural log of the count of firms (*lnExporterCount)* as several unions have an outsized number of firms.

Map 4: Firm distribution Dhaka Division and Surrounding



To evaluate the *prebendalism* logic we turn to constituency-level data on elections to the Bangladesh parliament, the Jatiya Sangsad. First, we map the ADM4 units into the 300 electoral districts of the Jatiya Sangsad. Then, using data from the Constituency-Level Elections Archive (CLEA), we code each ADM4 unit with a binary indicator that equals "1" if it was in a constituency that was represented by a government MP (*Gov MP*) from the 2008 election.[16] We find that, after the 2008 election, 4,453 (87%) of the ADM4 units are represented by a government MP. We use the results from the 2008 election as the parliamentary elections since that year have not had any meaningful opposition.[17] As such, the 2008 results give us an indication of those areas that did and did not support the ruling party when credible opposition existed.

[16] http://www.electiondataarchive.org accessed 17-06-2019.
[17] The 2014 election was not contested by the main opposition party and the 2018 election resulted in the ruling Awami League and allies winning 289 of 300 seats.

Our final data comes from the World Bank's subnational estimates of poverty[18] which utilize data from the 2010 Bangladesh Poverty Maps[19], the 2011 Census of Population and Housing[20] and the World Food Programme's 2012 undernutrition maps.[21] These data estimate poverty levels in the roughly 500 ADM3 units (upazilas) in Bangladesh. In a similar manner to that above, we map the poverty data from the ADM3 units onto the ADM4 units. We utilize several different estimation techniques and approaches in the robustness checks as these data have no variation for unions *within* a given upazila. For an indicator, we use the "extreme poverty headcount ratio" indicator which shows the percentage of the local population that lives below the official national lower poverty line.

While the AidData contains information on the timing of AfT projects, unfortunately we currently have no such data on the timing of either the establishment or start/resumption of exporting activity by the firms. As such, we are unable to use spatial-*temporal* approaches which might enable us to look for a *causal* relationship between AfT and exporting firm presence. In particular, we cannot say if the location of exporting firms preceded or succeeded the presence of the AfT project(s). That said, data from the World Bank's non-geographically representative 2013 Enterprise survey suggests that of the 364 exporting firms they surveyed, 213 (58.5%) were exporting and 257 (70.6%) were established prior to 2000, which precedes most AfT projects in the AidData database.[22] A geographically and sectorally representative survey of 787 firms from the exporter directory, conducted by ourselves from September to December 2019, finds that 346 (44%) of firms were established as of 2000. Thus, it appears likely that a significant majority of exporting firms would have already been in place at the time the AfT projects were allocated. Likewise, there is no temporal variation in the poverty maps, nor is there meaningful temporal variation in electoral data since 2008. Accordingly, this analysis should be understood as identifying correlations rather than causal effects. However, we believe that documenting co-location between AfT projects and exporting firms, government constituencies, and levels of poverty is still useful in understanding aid allocation behaviour and can form the basis of expectations for studies that are able employ causal inference approaches.

Our main estimation technique is a linear probability model. Despite the binary nature of our main outcome variable we use an OLS estimator with robust standard errors for ease of

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[18] Available at https://designstudio.worldbank.org/maps/2016/3323/res/data/zila_and_upazila_data.zip accessed 03-11-2019
[19] http://www.worldbank.org/en/news/feature/2014/09/30/poverty-maps accessed 03-11-2019
[20] https://international.ipums.org/international-action/sample_details/country/bd
[21] https://www.wfp.org/content/undernutrition-maps-bangladesh-2012
[22] https://login.enterprisesurveys.org/content/sites/financeandprivatesector/en/library/library-detail.html/content/dam/wbgassetshare/enterprisesurveys/economy/bangladesh/Bangladesh-2013-full-data.dta Accessed 05-11-2019

interpretation. We check our results to using non-linear estimators in the robustness section. We first present a baseline model with each indicator of allocation logic. We then introduce separate two-way interaction effects before modelling the full three-way interaction between exporting firm presence, political representation and poverty. In addition, in all models we include a measure of distance to the nearest major metropolitan area (either Dhaka or Chittagong). Our reduced form baseline model is:

$$(1) \quad Y_i = \beta_1 \cdot Exporter_{it} + \beta_2 \cdot Poverty_i + \beta_3 \cdot MP_i + \gamma \cdot Distance_i + \varepsilon_i$$

where Y is our binary indicator of area *i* having an AfT project. This outcome is regressed on our *Exporter, Poverty* and *MP* indicators and a measure of *Distance* of the area from the nearest metropolitan area of 500,000 or more people (effectively Dhaka or Chittagong).

Results

Our main results are presented in Table 1. The baseline model (1) shows that the measures of each of the allocation logics are positively associated with AfT projects and statistically significant at at least the 5% level. Substantively, the largest relationship is with exporting firms. The probability of an AfT project's presence in a given ADM4 unit is 10.5% higher when that ADM4 unit also has an exporting firm (p-value 0.000). That compares to a 3.2% increase being in an electoral district with a ruling party MP (p-value 0.017). The poverty headcount measure ranges from 0 to 50%, so the probability of an ADM4 unit having an AfT project is 5% higher when going from an area with the least amount of poverty to the highest amount (p-value 0.018).

We present the results from interaction models (2-5) graphically in order to illustrate the marginal effects of the interactions. The two-way interaction models are presented in Figure 1. The relationships between government representation and the presence of an exporting firm (Figures 1.1 and 1.3) show clear and positive interactions as shown in model 2. When an ADM4 unit has no ruling party representation, the marginal effect of an exporting firm on the probability of having an AfT project is statistically insignificant (p-value 0.675). However, when there is a ruling party MP, marginal effect of an exporting firm on the probability of an AfT project is 11.8% (p-value 0.000). Likewise, the marginal effect of an MP on AfT is only 2.4% and not significant (p-value 0.075) at the 5% level when there is no exporting firm in the ADM4 unit. However, this marginal effect rises to 16.5% and is statistically significant at the 1% level (p-value 0.003) when an exporting firm is also in the ADM4 unit.

The two-way interactions between the presence of large amounts of poverty and exporting firms (Figures 1.2 and 1.4) are equally stark, as shown in model 3. When poverty levels are at their lowest, the marginal effect of an exporting firm on increasing the probability of an AfT is statistically insignificant (p-value 0.258). However, in ADM4 units with the highest levels of extreme poverty, the marginal effect of an exporting firm on the probability of the presence of an AfT is over 35% and significant at the 1% level (p-value 0.001). Likewise, when there is no exporting firm in the ADM4 unit, the marginal effect of poverty on the presence of an AfT project is statistically insignificant (p-value 0.149). However, when there is an exporting firm, the marginal effect is 0.007 (p-value 0.004) meaning that an increase from the lowest to highest level of poverty would increase the probability of an AfT project in the ADM4 unit by approximately 35%.

In contrast, as shown in model 4, any interactive relationship between government representation and poverty is largely absent. When viewing the marginal effects graphically (Figures 1.5 and 1.6) one can see that while the statistical significance of the marginal effect of poverty on the presence of an AfT project increases when the ADM4 unit also has a ruling party MP, the magnitude of that effect is nearly unchanged. Similarly, while the marginal effect of an MP on AfT is only statistically significant at the areas of the greatest density in the distribution of poverty (see poverty histogram in Figure A.1 in the Appendix), the magnitude of the marginal effect is mostly unchanged across the range of poverty ratios (Figure 1.6).

However, turning to the three-way interactions in Figure 2 we see the strong support for the role of multiple logics in AfT allocation. For each indicator, the largest marginal effects on the likelihood of an AfT project in the same ADM4 unit are the highest when both of the other indicators are at their largest values. In ADM4 units with the highest levels of poverty and representation by a ruling party MP (Figure 2.1), the marginal effect of an exporting firm on the presence of an AfT project is an over 40% increase in probability. Likewise, when an exporting firm is present in an ADM4 unit with the highest levels of poverty (figure 2.2), the marginal effect of representation by a ruling party MP on the probability of an AfT project is 43.6%. Finally, the marginal effect of extreme poverty is 0.008 when that ADM4 unit has both a ruling party MP and an exporting firm (Figure 2.3). This again means that increasing poverty from the least to the greatest increases the probability of an AfT project in that ADM unit by 40%.

Extensions and Robustness Checks

We investigate several extensions to our baseline model utilizing additional features of the data in Table 2. In the first extension, rather than using binary indicators for AfT and exporting firms, we take advantage of the count we have of each at the ADM4 level. As mentioned above, we find from 0 to 9 AfT projects and from 0 to 266 exporting firms at the ADM4 level. In the first instance (models 6 and 7), we use the natural log of each of these counts plus one, in a linear regression. In the second instance (models 8 and 9), we used the untransformed count of AfT projects in a negative binomial model since the data shows overdispersion along with the log count of exporting firms. Finally, as the AfT data is also zero-inflated (with "0" values in 4,394 of the 5,160 ADM4 units), we employ a zero-inflated negative binomial estimator (models 10 and 11) where we use the distance to a city (*City Distance*) with a population of 500,000 or greater measure in the first-stage inflation model, with the assumption that sites further away from the major metropolitan areas will be less likely to have any AfT project. In the second-stage, count, model we use all variables as we would expect distance from the city to also impact the count of AfT projects. Summary statistics and histograms of the AfT and firm counts are available in the online appendix. We present only the baseline and three-way interaction models and the count stage of the ZNIB model.

Table 1: AfT Project Presence (Binary)

VARIABLES	(1) Baseline	(2) Firm*MP	(3) Firm*Poverty	(4) MP*Poverty	(5) Firm*MP*Poverty
Poverty	0.001**	0.001**	0.001	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Exporter	0.105***	-0.022	0.037	0.105***	-0.030
	(0.023)	(0.053)	(0.032)	(0.023)	(0.065)
MP	0.032**	0.025*	0.035**	0.028	0.027
	(0.014)	(0.014)	(0.014)	(0.023)	(0.024)
Distance to City	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exporter*MP		0.140**			0.072
		(0.058)			(0.073)
Exporter*Poverty			0.006**		0.000
			(0.002)		(0.004)
MP*Poverty				0.000	-0.000
				(0.001)	(0.001)
Exporter*MP*Poverty					0.007
					(0.004)
Observations	4,913	4,913	4,913	4,913	4,913
Prob > F	0.000	0.000	0.000	0.000	0.000
R-squared	0.015	0.015	0.017	0.015	0.018

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

Table 2: Extensions (Counts and Firm Sector)

VARIABLES	(6) lnCount	(7) lnCount 3-way	(8) Neg Binomial	(9) NB 3-way	(10) ZINB	(11) ZINB 3-way	(12) Apparel	(13) Apparel 3-Way	(14) Non-Apparel	(15) Non-Apparel 3-Way
Exporter	0.061***	-0.003	0.360***	-0.363	0.386***	-0.358	0.105***	-0.045	0.121***	0.096
	(0.013)	(0.072)	(0.066)	(0.808)	(0.062)	(0.802)	(0.026)	(0.080)	(0.029)	(0.133)
MP	0.030**	0.034*	0.298**	0.551**	0.321**	0.599**	0.032**	0.026	0.034**	0.032
	(0.012)	(0.020)	(0.144)	(0.245)	(0.129)	(0.241)	(0.014)	(0.023)	(0.014)	(0.023)
Poverty	0.001**	0.001	0.010**	0.018*	0.010**	0.020*	0.001**	0.001	0.001**	0.001
	(0.000)	(0.001)	(0.004)	(0.011)	(0.004)	(0.011)	(0.000)	(0.001)	(0.000)	(0.001)
Distance to City	-0.000***	-0.000***	-0.002***	-0.002***	0.001		-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)		(0.000)	(0.000)	(0.000)	(0.000)
Exporter*MP		0.041		0.579		0.611		0.110		-0.029
		(0.074)		(0.813)		(0.806)		(0.088)		(0.138)
Exporter*Poverty		0.004		0.074		0.071		-0.001		-0.004
		(0.007)		(0.076)		(0.077)		(0.003)		(0.006)
MP*Poverty		-0.000		-0.013		-0.015		0.000		-0.000
		(0.001)		(0.012)		(0.012)		(0.001)		(0.001)
Exporter*MP*Poverty		-0.000		-0.052		-0.052		0.006		0.011*
		(0.008)		(0.076)		(0.078)		(0.004)		(0.007)
Prob > F(χ^2)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	4,913	4,913	4,913	4,913	4,913	4,913	4,913	4,913	4,913	4,913
R-squared	0.018	0.020					0.013	0.015	0.014	0.016

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

Figure 1: Two-Way Interactions Marginal Effects

Figure 1.1

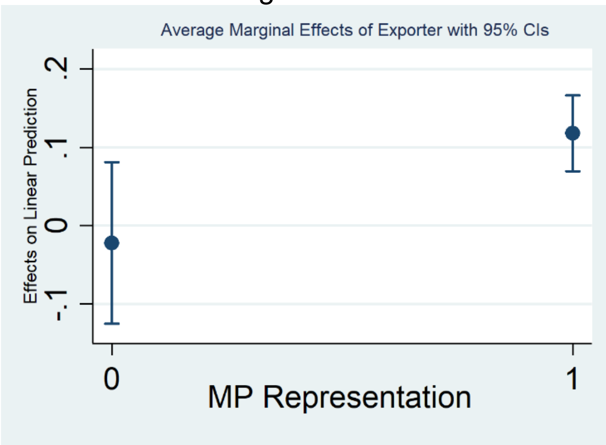


Figure 1.2

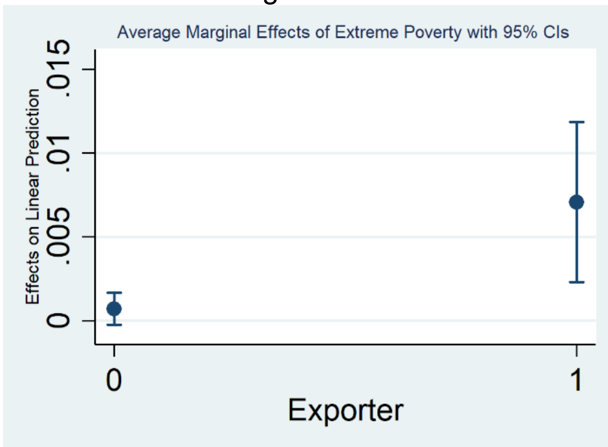


Figure 1.3

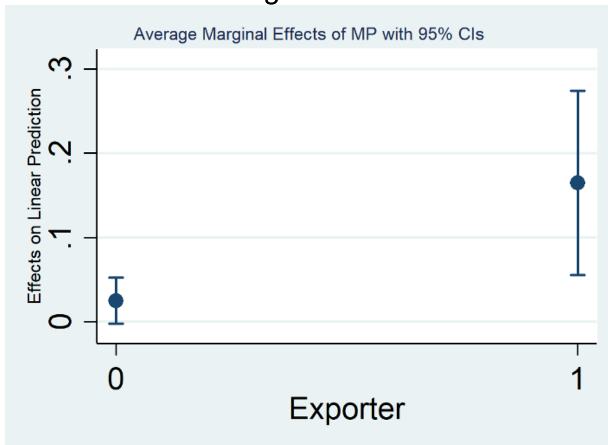


Figure 1.4

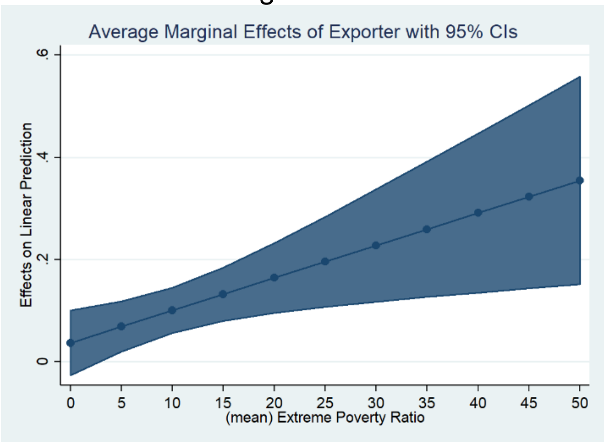


Figure 1.5

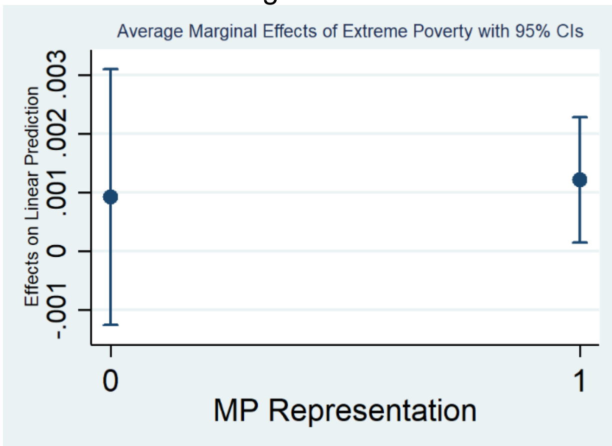


Figure 1.6

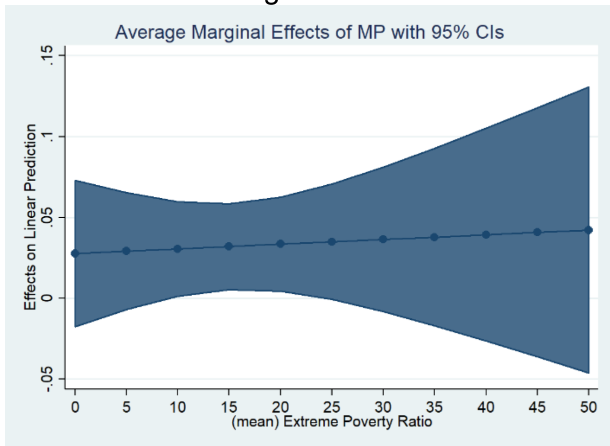


Figure 2: Three-Way Interactions Marginal Effects (Baseline Models)

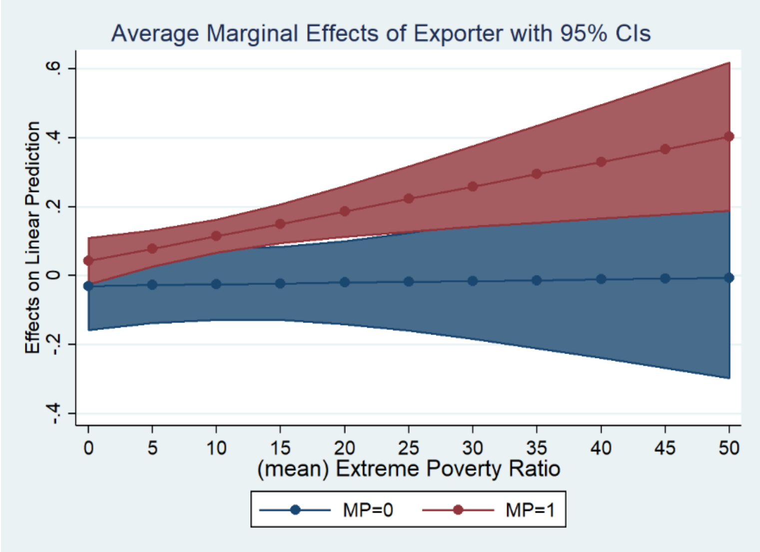


Figure 2.1

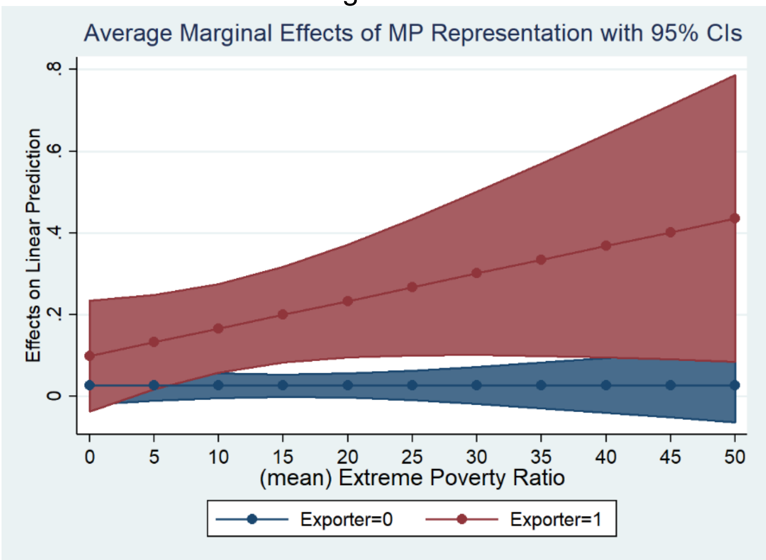


Figure 2.2

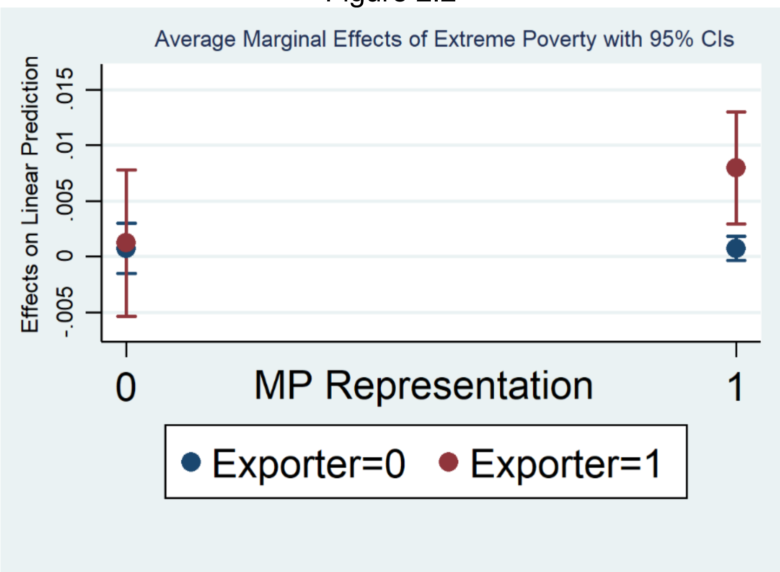


Figure 2.3

Figure 3: Three-Way Interactions Marginal Effects (Extension Models)

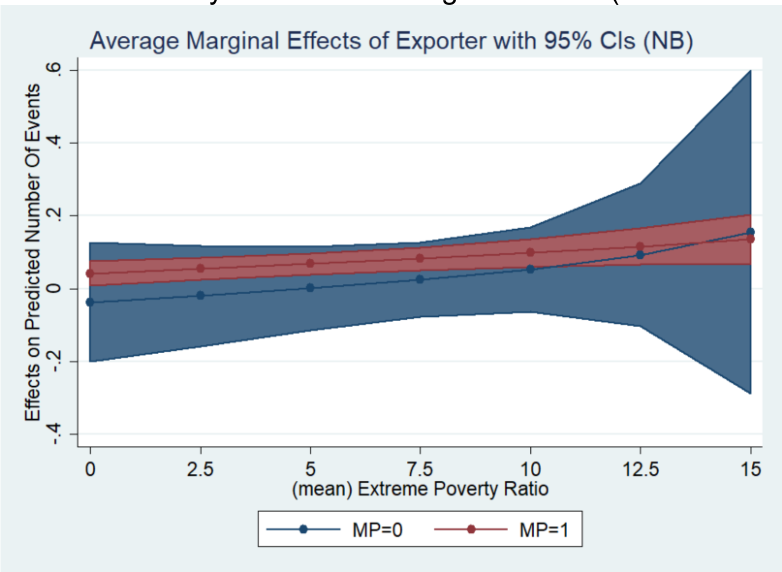


Figure 3.1

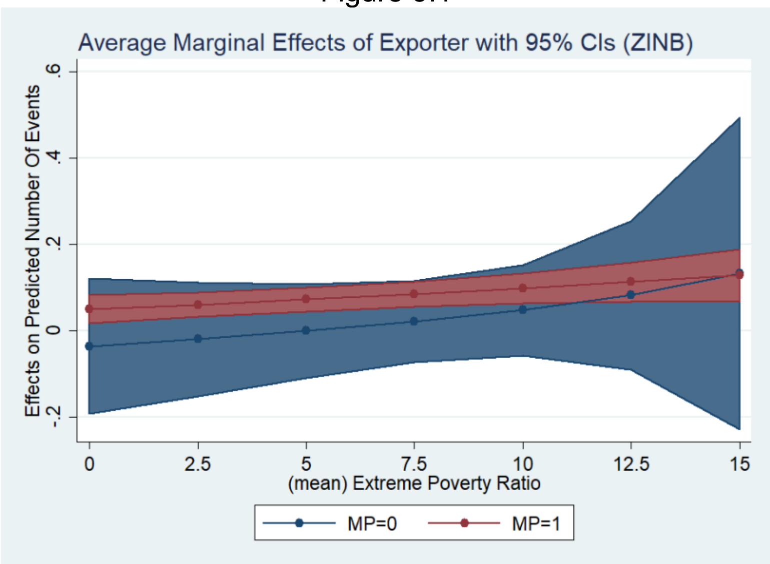


Figure 3.2

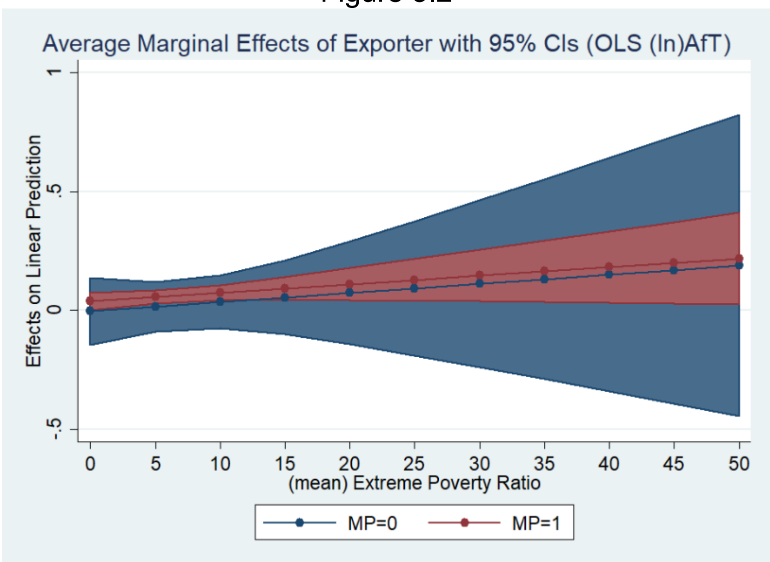


Figure 3.3

In all instances of the baseline model (models 6, 8 and 10), all three factors (exporter, MPs and poverty) again are positively associated with the (ln) count of AfT projects in ADM4 units at at least the 5% level of significance. Turning to the interaction models (7, 9 and 11), the main finding from the binary specifications is maintained. As shown in figure 3 the marginal effect of the number of exporting firms on the number of AfT projects is only statistically significant when the ADM4 unit also has ruling party MP representation and is increasingly large as the ratio of extreme poverty increases.

As a second extension, we take advantage of the fact that our firm data is coded by sector. We use this information to split our sample and reconstruct our firm indicators based on the "apparel" and "non-apparel" sectors. We find that the main results are maintained in both the baseline and three-way models for both the apparel (models 12 and 13) and non-apparel (models 14 and 15) sectors. The interaction results are shown graphically in the online appendix for apparel (figure A.11) and non-apparel (figure A.12), respectively.

We subject the main findings above to several robustness checks with full tables and figures available in the online appendix. As our main analysis used linear probability models for ease of interpretation, we also check our results using a non-linear logit estimator (Table A.2). The main results are maintained in both the baseline model (3) and with the three-way interactions as shown in figure A.4.

Next, we consider the fact that there are two major economic centres in Bangladesh: Dhaka and, to a lesser extent, Chittagong. Accordingly, we check if our results are robust to the exclusion of these two areas from the analysis in Table A.2. Here we see that, in the baseline model (1), the coefficient on poverty is no longer statistically significant at the 10% level (p-value 0.121) when excluding Dhaka and Chittagong. However, turning to the three-way interaction (model 2), we do again see a positive and significant effect of poverty (p-value 0.010) on the presence of an AfT project when the ADM4 unit also has an exporting firm and a ruling party MP in Figure A.5. We also see that the three-way interactions for MPs and exporting firms remain consistent.

In our second robustness check we consider the fact that, as noted above, our data is nested and our poverty measure does not vary at the ADM4 level when accounting for the ADM3 level. This is likely to introduce spatial dependence into our models and, indeed, calculating the Moran's I statistic on the residuals of Model 1 (Table A.5 in the Online Appendix) indicates the presence of spatial autocorrelation. Thus, in our first robustness check, we create spatial weighting matrices ***W*** and use those to estimate spatial-lag, spatial-autocorrelation SARAR models in Table A.3. We create ***W*** matrices using both inverse-distance (model 1) and ADM4 contiguity (model 3) weightings. The results from these baseline models are substantively similar to those of the OLS specifications (models 2 and 4). When using the contiguity weighting (model 3), poverty, exporters and MP are all positively associated at a significance level of at least 5% with the presence of an AfT project in an ADM4 unit. When using the inverse-distance weighting the coefficient on poverty is no longer statistically significant at the 10% level (p-value 0.193), similar to the Dhaka/Chittagong exclusion models in table A.2.

To further address the fact that poverty is measured at the ADM3 level, we also run models where we include dummy variables for each ADM1 (Division) and ADM2 (District) unit in order to account for unobserved characteristics at those levels of aggregation in Table A.3. In the baseline model (5), the positive and significant results on exporters and MPs remain, but the coefficient on poverty is again insignificant (p-value 0.699). This result perhaps suggests that there is insufficient intra-ADM2 level variation in poverty, or, in other words, poverty tends to be clustered by district (Khatun 2001). Accordingly, to more directly capture this, we use a multi-level mixed effects model where we nest our ADM4 units into their higher administrative counterparts. Once again, in the baseline specification (model 8) poverty is no longer statistically significant at the 10% level (p-value 0.142). However, when introducing the three-way interactions in both the ADM1 and 2 fixed effects model (6) and multi-level mixed effects model (7) we again find that, as with our count models above, the coefficient on poverty is positive and significant (p-value 0.014) conditional on there being both an exporting firm and government representation in the ADM4 unit mirroring our main result above. The three-way interactions for MPs and exporting firms, respectively, also remain similar to the main results presented above. These results for the fixed and mixed effects are shown graphically in figures A.6 and A.7, respectively.

Finally, we test the sensitivity of our results to different definitions and precisions of AfT in Table A.4. First, we trim what we classify as “thin” AfT to only those projects very clearly building economic infrastructure or explicitly aimed at increasing export capacity. This reduces our dataset to 86 projects at 834 locations. Similarly, we test if our AfT results differ in any way from results using all geo-coded aid projects in Bangladesh. This expands our data to 159 projects at 3,680 locations at precision code 3 or better. Using these outcome measures, the coefficient on poverty is not significant in either the baseline model with all aid (p-value 0.884) or the “thin” AfT (p-value 0.938) as in many of the models above. Likewise, the coefficient on MPs is not significant at the 10% level (p-value 0.172) in the “thin” AfT model (3). The presence of exporting firms, however, remains significant at the 1% level in both baseline models. Turning to the three-way interactions, we once again see a conditional effect for all of the measures in both the “all aid” model (figure A.8) and the “thin AfT” model (figure A.9). In particular, the marginal effect of poverty is positive and significant at the 1% level in both the “all aid” (p-value 0.001) and “any aid” (p-value 0.001) when an ADM4 unit has both exporting firms and ruling party representation. Likewise, the marginal effect of both exporting firms and ruling party MPs is increasing in poverty and larger when the other factor is present, respectively. These interactive results both add to the robustness of our main finding, but also suggest that multiple logics may affect the allocation of *all* types of aid, not just AfT. Finally, we restrict our original AfT projects to only those at precision code “2” or better. The results using this paring are substantively unchanged as shown in models 4 and 5 and figure A.10.

Conclusions

We investigated if the geographic patterns of aid for trade allocation in Bangladesh are consistent with functional, prebendalist and/or poverty-based logics. Overall, using novel data on the locations of over 11,000 exporting firms and over 1,000 aid for trade project locations across over 5,000 administrative units, we find evidence of correlations between the presence of exporting firms (functional), ruling party representation (predendalist) and extreme poverty and the location of Aid for Trade projects. However, we find both statistically stronger and substantively larger marginal effects when considering the *interaction* between these three logics. Locations with high levels of poverty, ruling party representation *and* exporting firms have a probability of also having an AfT project that is over 150% larger than the baseline probability rate.

Our results are robust to a number of different characterizations of the outcome variable, specification types, estimators, and controlling for the presence of spatial autocorrelation. Our most sensitive finding is that on poverty, which is not robust in all of the baseline, non-interactive, models. That said, when considering the conditional, interactive effect, we do find a positive relationship between AfT allocation and high levels of poverty across the entire range of specifications. However, this result perhaps points towards poverty being the “least among equals” in terms of allocation logics, which may square our findings with those who have found no evidence of pro-poor considerations in aid allocation (Briggs 2017, 2018a, 2018b) Finally, we stress that, due to the absence of temporal variation and random assignment, our results cannot be taken as causal, but instead are patterns that may be indicative of, or consistent with, established logics of aid allocation. Exploring these findings with data that permits (quasi)causal inference would be a useful extension.

Collectively, these findings speak to a political economy of sub-national aid allocation that is not *either-or* in terms of donor control and recipient capture. Patterns of aid allocation may serve *multiple* political economy functions – they may both satisfy donor preferences for *functionality* or *need* but also be useful to recipient *prebendalist* interests. Indeed, such a nuanced outcome is precisely what might be expected from recent work which suggests that the coordination and ultimately allocation is a carefully crafted dance and compromise between two parties (Swedlund 2017).

References

AidData. 2016. BangladeshSelectDonors_GeocodedResearchRelease_Level1_v1.1.1 geocoded dataset. Williamsburg, VA and Washington, DC: AidData. Accessed on [date]. http://aiddata.org/research-datasets.

Amin, S. B., & Murshed, M. (2017). An empirical analysis of multivariate causality between electricity consumption, economic growth and foreign aid: Evidence from Bangladesh. *The Journal of Developing Areas*, *51*(2), 369-380.

Brazys, S., Heaney, P., & Walsh, P. P. (2015). Fertilizer and votes: Does strategic economic policy explain the 2009 Malawi election?. *Electoral Studies*, *39*, 39-55.

Brazys, S., & Lightfoot, S. (2016). Europeanisation in Aid for Trade: the impact of capacity and socialisation. *European Politics and Society*, *17*(1), 120-135.

Brazys, Samuel Rueckert and Vadlamannati, Krishna Chaitanya and Song, Tianyang, Which Wheel Gets the Grease? Constituent Agency and Sub-national World Bank Aid Allocation (February 5, 2019). Available at SSRN: https://ssrn.com/abstract=3329507 or http://dx.doi.org/10.2139/ssrn.3329507

Briggs, R. C. (2014). Aiding and abetting: project aid and ethnic politics in Kenya. *World Development*, *64*, 194-205.

Briggs, R. C. (2017). Does foreign aid target the poorest?. *International Organization*, *71*(1), 187-206.

Briggs, R. C. (2018). Poor targeting: A gridded spatial analysis of the degree to which aid reaches the poor in Africa. *World Development*, *103*, 133-148.

Briggs, R. C. (2018). Leaving No One Behind? A New Test of Subnational Aid Targeting. *Journal of International Development*, *30*(5), 904-910.

Carnegie, A., Howe, K, Lichtenheld, A., and Mukhopadhyay, D. (2019). The Effects of Foreign Aid on Rebel Governance: Evidence from a Large-Scale U.S. Aid Program in Syria. AidData Working Paper #77. Williamsburg, VA: AidData at William & Mary.

Civellia, A., Horowitz, A., & Teixeira, A. (2018). Foreign aid and growth: A Sp P-VAR analysis using satellite sub-national data for Uganda. *Journal of Development Economics, 134*, 50-67.

Dietrich, S., Mahmud, M., & Winters, M. S. (2018). Foreign Aid, Foreign Policy, and Domestic Government Legitimacy: Experimental Evidence from Bangladesh. *The Journal of Politics, 80*(1), 133-148. doi:10.1086/694235

Dionne, K. Y. (2017). *Doomed interventions: The failure of global responses to AIDS in Africa*. Cambridge University Press.

Dreher, A., Fuchs, A., Hodler, R., Parks, B. C., Raschky, P. A., & Tierney, M. J. (2019). African leaders and the geography of China's foreign assistance. *Journal of Development Economics*.

Dunning, T., & Harrison, L. (2010). Cross-cutting cleavages and ethnic voting: An experimental study of cousinage in Mali. *American Political Science Review*, *104*(1), 21-39.

GED (2013) *Millennium Development Goals: Bangladesh Progress Report 2013*, Dhaka: Planning Commission, General Economics Division, Government of Bangladesh.

Isaksson, A. (2019). Chinese aid and local ethnic identification. AidData Working Paper #80. Williamsburg, VA: AidData at William & Mary.

Alam, S. and Iqbal, K. (2016), "Dynamics of Regional Poverty and Real Wages: Policy Implications for Development Interventions" in Davine J. et al. edited, Extreme Poverty, Growth and Inequality in Bangladesh, Practical Action Publishing, UK,

Isaksson, A. S., & Kotsadam, A. (2018). Chinese aid and local corruption. *Journal of Public Economics*, *159*, 146-159.

Jablonski, R. S. (2014). How aid targets votes: the impact of electoral incentives on foreign aid distribution. *World Politics*, *66*(2), 293-330.

Khatun, T. (2001). District-based measurement of human poverty in Bangladesh. *The Bangladesh Development Studies*, *27*(3), 91-109.

Kai Gehring, Lennart Kaplan, and Melvin H. L. Wong. 2019 Aid and Conflict at the Sub-National Level: Evidence from World Bank and Chinese Development Projects in Africa. AidData Working Paper #70. Williamsburg, VA: AidData at William & Mary

Knutsen, T., & Kotsadam, A. (2020). The political economy of aid allocation: Aid and incumbency at the local level in Sub Saharan Africa. *World Development*, *127*, 104729.
Kotsadam, A., Østby, G., Rustad, S. A., Tollefsen, A. F., & Urdal, H. (2018). Development aid and infant mortality. Micro-level evidence from Nigeria. *World Development*, *105*, 59-69

Lewis, P. (1996). From prebendalism to predation: the political economy of decline in Nigeria. *The Journal of Modern African Studies*, *34*(1), 79-103.

Lordemus, S. (2019). Are donors targeting the greatest health needs? Evidence from mining sites in the D.R.Congo. AidData Working Paper #82. Williamsburg, VA: AidData at William & Mary.

Marty, R., Dolan, C. B., Leu, M., & Runfola, D. (2017). Taking the health aid debate to the subnational level: the impact and allocation of foreign health aid in Malawi. *BMJ global health*, *2*(1), e000129.

Masaki, T. (2018). The political economy of aid allocation in Africa: Evidence from Zambia. *African Studies Review*, *61*(1), 55-82.

Milner, H. V., Nielson, D. L., & Findley, M. G. (2016). Citizen preferences and public goods: Comparing preferences for foreign aid and government programs in Uganda. *The Review of International Organizations*, *11*(2), 219-245.

Mullan, K., Sills, E., & Bauch, S. (2014). The reliability of retrospective data on asset ownership as a measure of past household wealth. *Field methods*, *26*(3), 223-238.

Rahman, M. S., & Giessen, L. (2017). Formal and informal interests of donors to allocate aid: Spending patterns of USAID, GIZ, and EU forest development policy in Bangladesh. *World Development*, *94*, 250-267.
Sawada, Y., Mahmud, M., & Kitano, N. (2018). *Economic and Social Development of Bangladesh*. Springer.

Sen, B. and Ali, Z. (2015) Ending Extreme Poverty in Bangladesh during the Seventh Five Year Plan: Trends, Drivers and Policies, Background Paper, Seventh Five Year Plan, Dhaka: Planning Commission, Government of Bangladesh.

SOG. 2014. The State of Governance Bangladesh 2013: Democracy Party Politics. BRAC Institute of Governance and Development, BRAC University.

Swedlund, H. J. (2017). *The development dance: How donors and recipients negotiate the delivery of foreign aid*. Cornell University Press.

Szeftel, M. (2000). Clientelism, corruption & catastrophe. *Review of African Political Economy*, *27*(85), 427-441.

Online Appendix

Table A1: Summary Statistics

	(1)					
	count	mean	sd	Var	min	max
anyaft	5161	.1486146	.3557426	.1265528	0	1
countaft_ID	5160	.2153101	.6431216	.4136054	0	9
anyfirm	5161	.0877737	.2829929	.080085	0	1
countfirms~D	5160	.8366279	7.185511	51.63157	0	266
ga	5130	.8680312	.3384898	.1145754	0	1
xpov	4921	18.37555	10.46685	109.555	0	50
km_to_nid	5159	142.6229	75.16861	5650.32	.5214793	384.2276
N	5161					

Table A2: Robustness 1 (Logit and Excluding Dhaka/Chittagong)

VARIABLES	(1) Ex Dhaka/Chit	(2) Ex Dk/Cht 3-way	(3) Logit	(4) Logit 3-way
Exporter	0.137***	0.006	0.671***	-0.315
	(0.031)	(0.084)	(0.134)	(0.797)
MP	0.036**	0.029	0.292**	0.267
	(0.015)	(0.026)	(0.130)	(0.235)
Poverty	0.001	0.001	0.010**	0.008
	(0.001)	(0.001)	(0.004)	(0.010)
Distance to City	-0.000***	-0.000***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.001)	(0.001)
Exporter*Poverty		-0.001		0.005
		(0.004)		(0.036)
MP*Poverty		-0.000		-0.001
		(0.001)		(0.011)
Exporter*MP		0.005		0.628
		(0.108)		(0.821)
Exporter*MP*Poverty		0.011*		0.030
		(0.006)		(0.038)
Prob > F	0.000	0.000	0.000	0.000
Observations	4,480	4,480	4,913	4,913
R-squared	0.015	0.018		

Table A.3 Spatial Robustness Checks

VARIABLES	(1) SARAR (Inv Dist)	(2) OLS (Inv Dist)	(3) SARAR (Contig)	(4) OLS (Contig)	(5) ADM1-2 FE	(6) ADM1-2 FE 3-Way	(7) Multi-level Mixed 3-Way	(8) Multi-level Mixed
Exporter	0.136***	0.105***	0.088***	0.097***	0.115***	-0.032	-0.033	0.117***
	(0.022)	(0.023)	(0.018)	(0.023)	(0.026)	(0.068)	(0.065)	(0.028)
MP	0.039**	0.032**	0.027**	0.030**	0.045**	0.059*	0.033***	0.042**
	(0.017)	(0.014)	(0.014)	(0.014)	(0.019)	(0.032)	(0.012)	(0.018)
Poverty	0.001	0.001**	0.001**	0.001**	0.000	0.001	0.001	0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)
Distance to City	-0.001**	-0.000***	-0.000***	-0.000***	0.001**	0.001**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exporter*Poverty						-0.001	-0.000	
						(0.003)	(0.004)	
MP*Poverty						-0.001	0.000	
						(0.002)	(0.000)	
Exporter*MP						0.095	0.099	
						(0.077)	(0.075)	
Exporter*MP*Poverty						0.006	0.006	
						(0.004)	(0.005)	
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	4,912	4,912	4,728	4,728	4,913	4,913	4,913	4,913
R-squared		0.014		0.015	0.047	0.049		
ADM1 FE					YES	YES		
ADM2 FE					YES	YES		

Table A.4 Alternate Aid Definitions

VARIABLES	(1) Any Aid	(2) Any Aid 3-way	(3) Thin AfT	(4) Thin AfT 3-way	(5) AfT PC2	(6) AfT PC2 3-way
Exporter	0.127***	-0.073	0.080***	-0.123***	0.095***	-0.028
	(0.026)	(0.088)	(0.022)	(0.024)	(0.023)	(0.064)
MP	0.047***	0.035	0.017	0.002	0.031**	0.020
	(0.017)	(0.031)	(0.013)	(0.022)	(0.013)	(0.023)
Poverty	-0.000	-0.001	-0.000	-0.001	0.001**	0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Distance to City	-0.000	-0.000	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exporter*MP		0.125		0.133***		0.080
		(0.095)		(0.040)		(0.073)
Exporter*Poverty		0.002		0.004		0.001
		(0.005)		(0.003)		(0.004)
MP*Poverty		0.000		0.000		0.000
		(0.001)		(0.001)		(0.001)
Exporter*MP*Poverty		0.007		0.005		0.004
		(0.006)		(0.004)		(0.004)
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
Observations	4,913	4,913	4,913	4,913	4,913	4,913
R-squared	0.009	0.012	0.019	0.025	0.013	0.015

Table A.5 Moran's I on residuals from model 1

Moran's I spatial correlogram

Distance bands	I	E(I)	sd(I)	z	p-value*
(1-2]	0.003	-0.000	0.000	7.692	0.000
(1-3]	-0.002	-0.000	0.000	-7.473	0.000
(1-4]	-0.004	-0.000	0.000	-20.742	0.000

*1-tail test

Figure A.1 Extreme Poverty Ratio Histogram

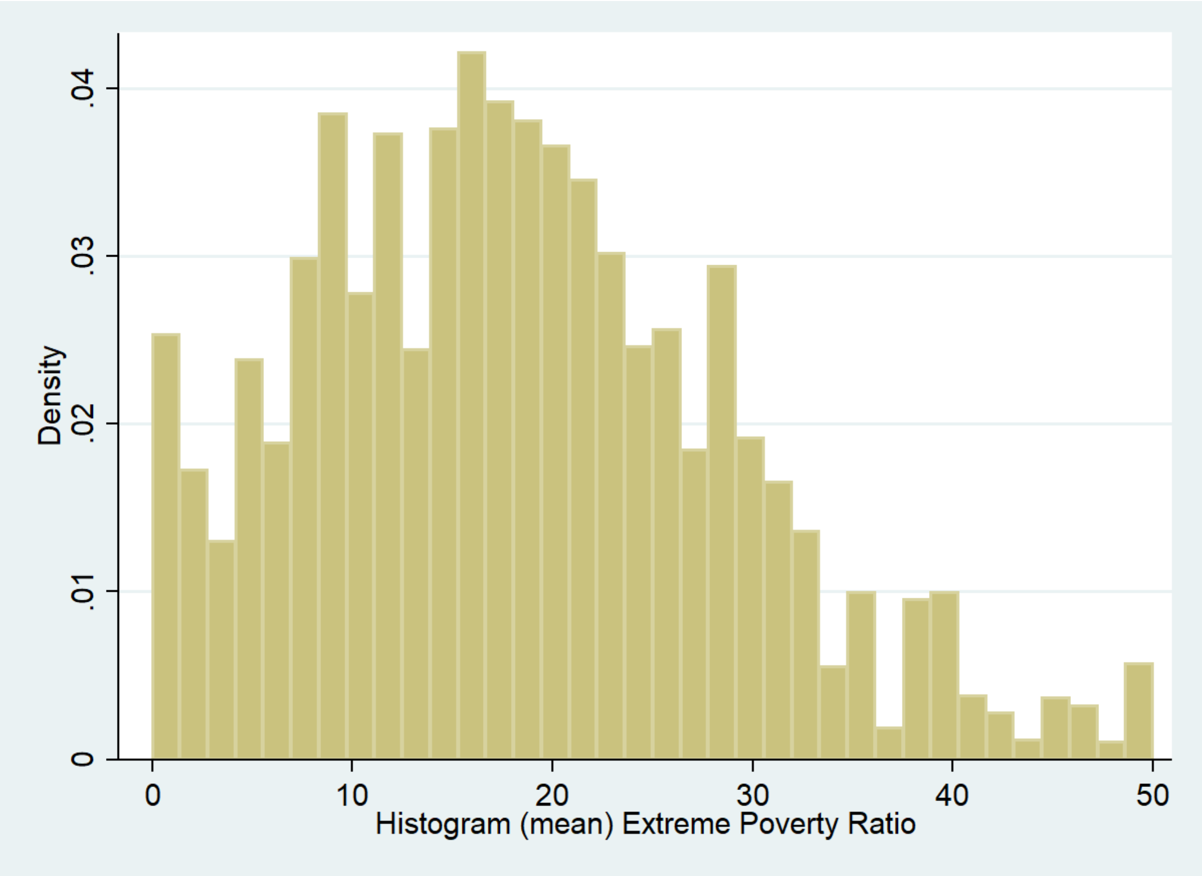


Figure A.2 Histogram of AfT Count (ADM4)

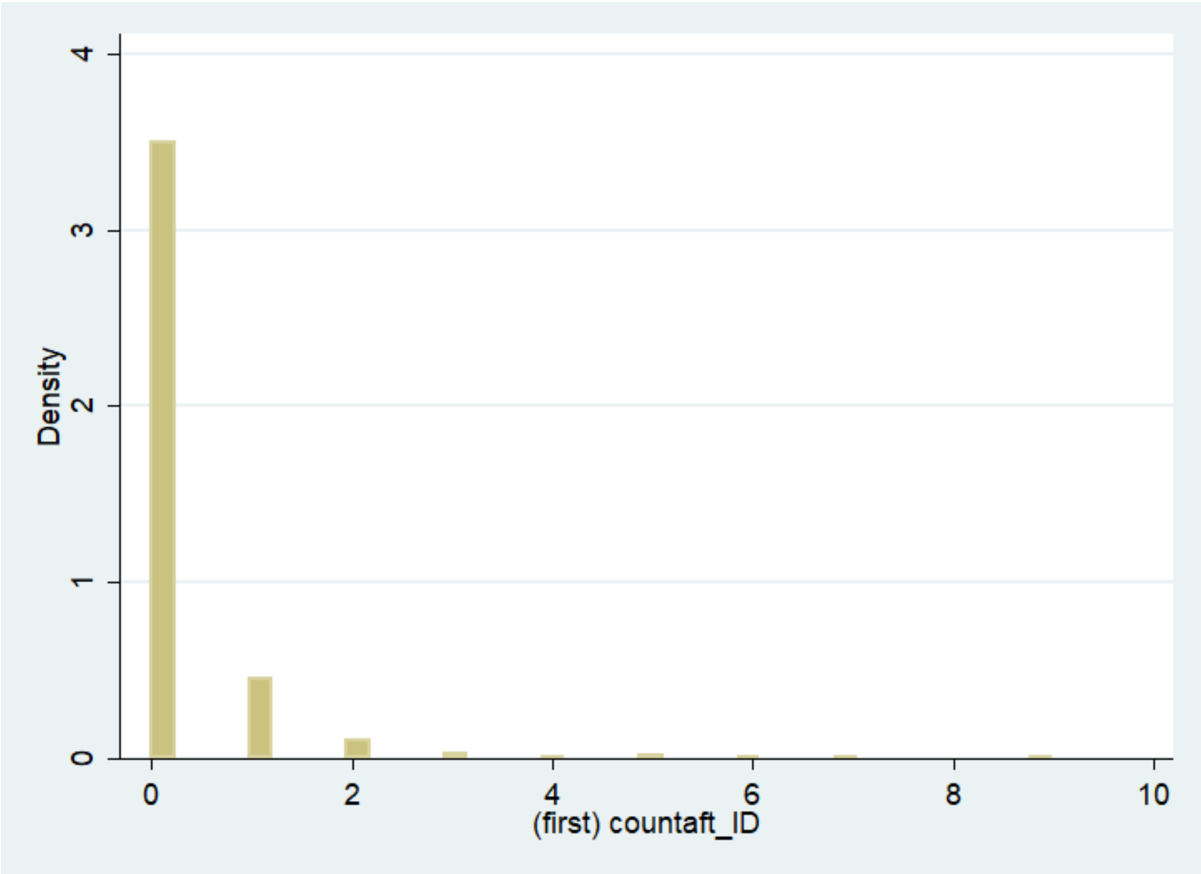


Figure A.3 Histogram Count Exporting Firms (ADM4)

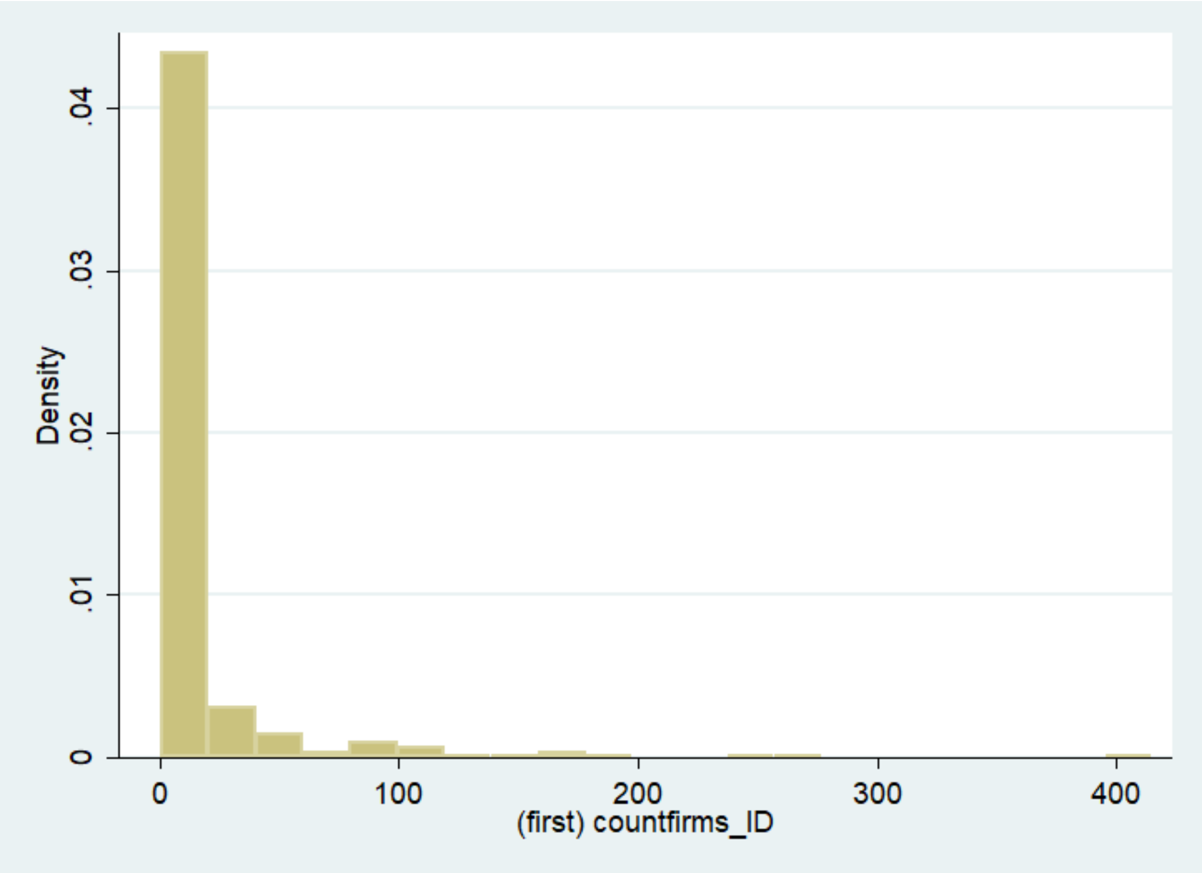


Figure A.4: Three-Way Interactions (Logit)

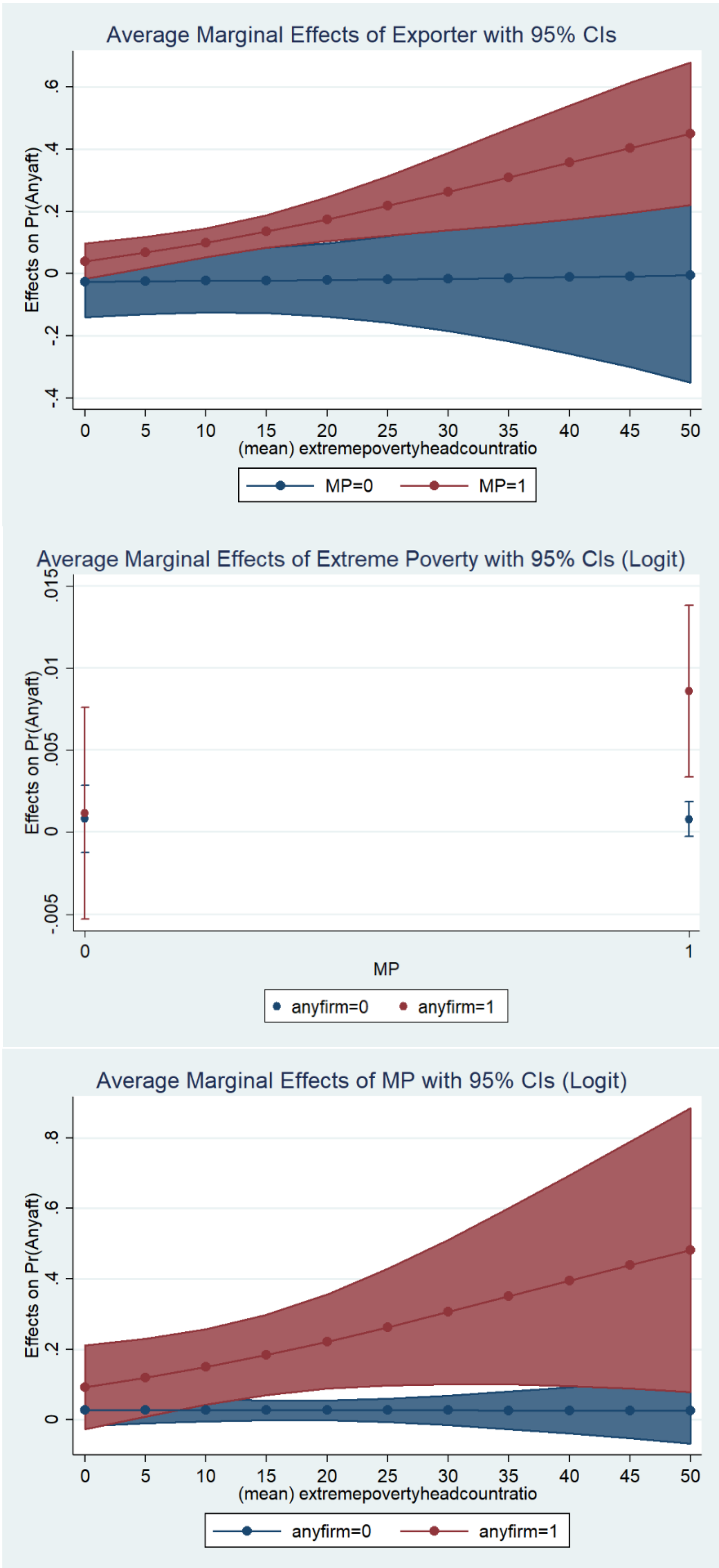


Figure A.5: Three-Way Interactions (Ex Dhaka/Chittagong)

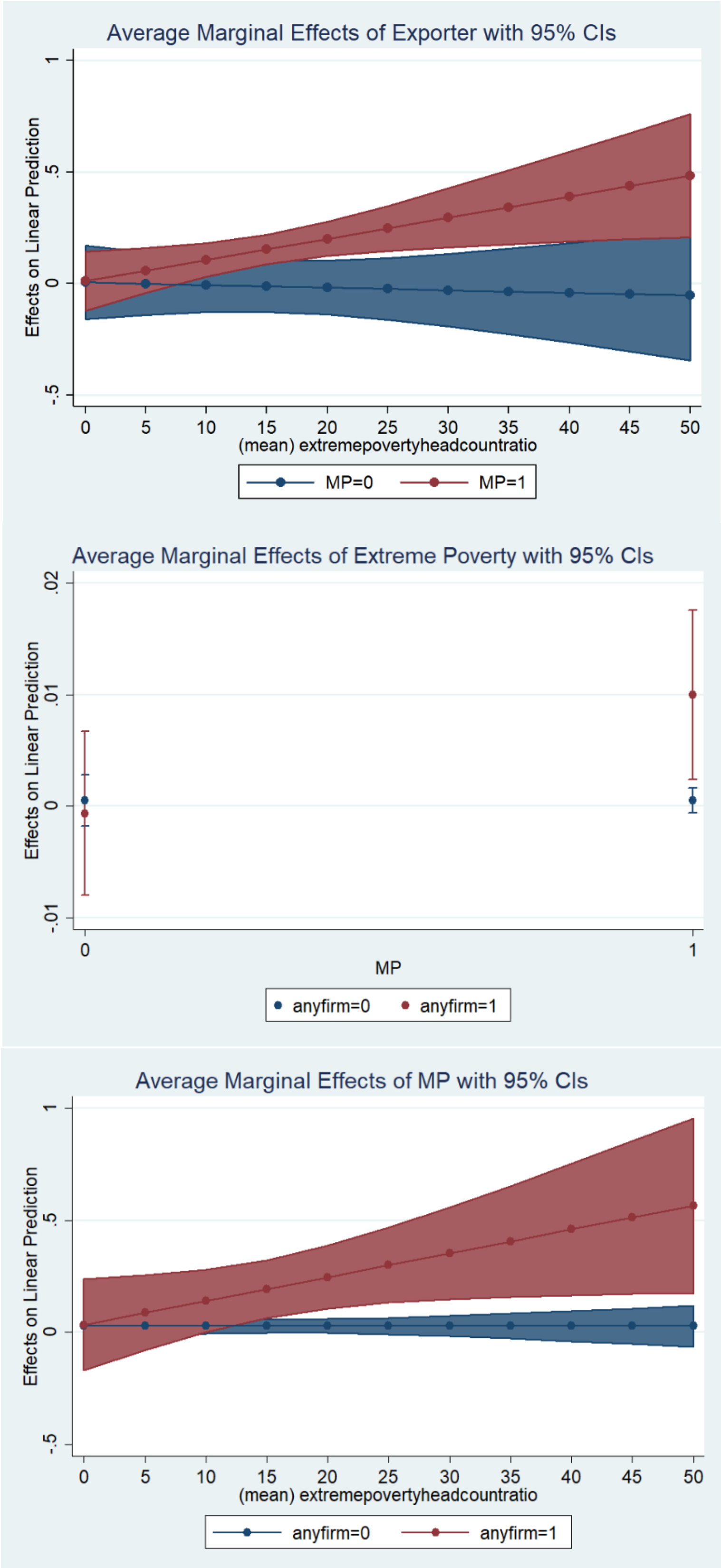


Figure A.6: Three-Way Interactions (ADM1 and 2 Fixed Effects)

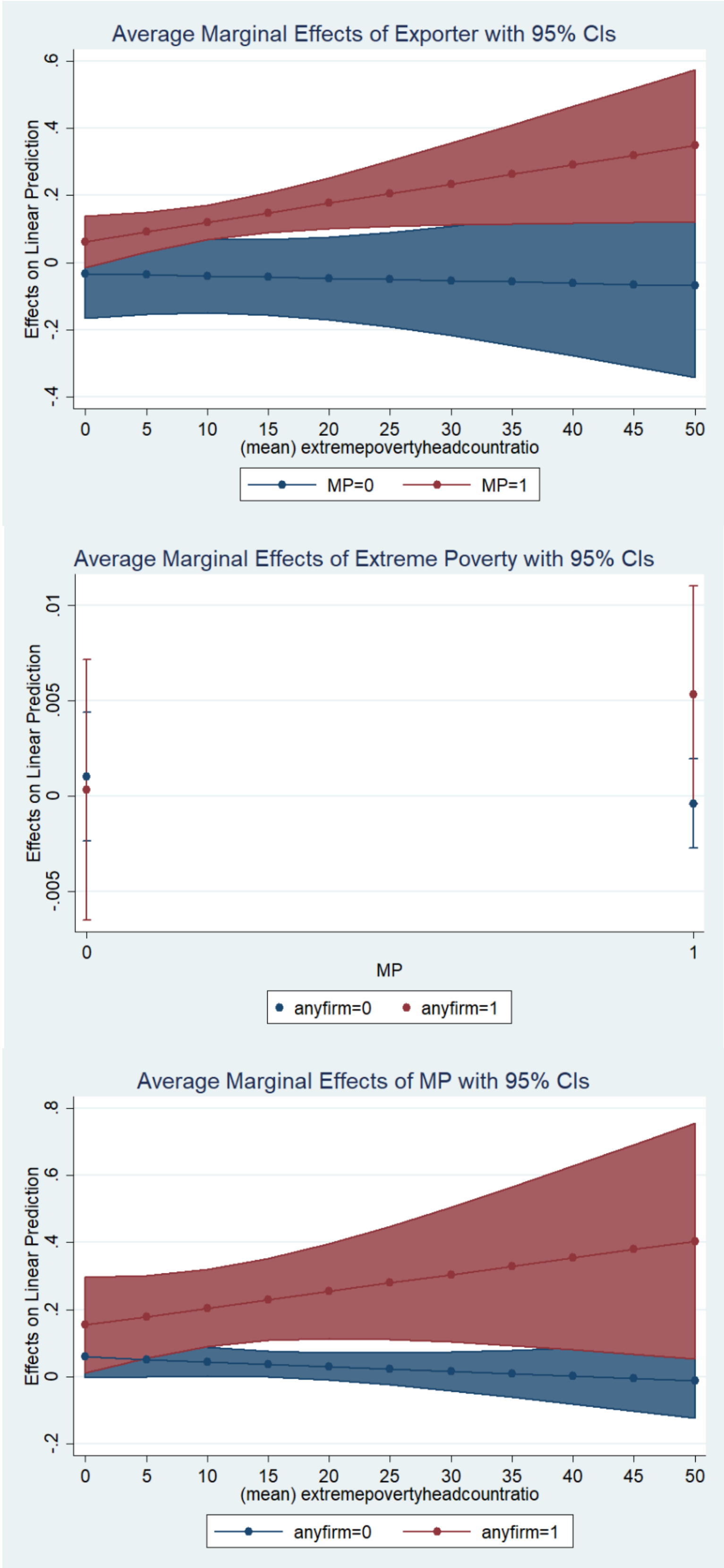


Figure A.7: Three-Way Interactions (Multi-level Mixed Effects)

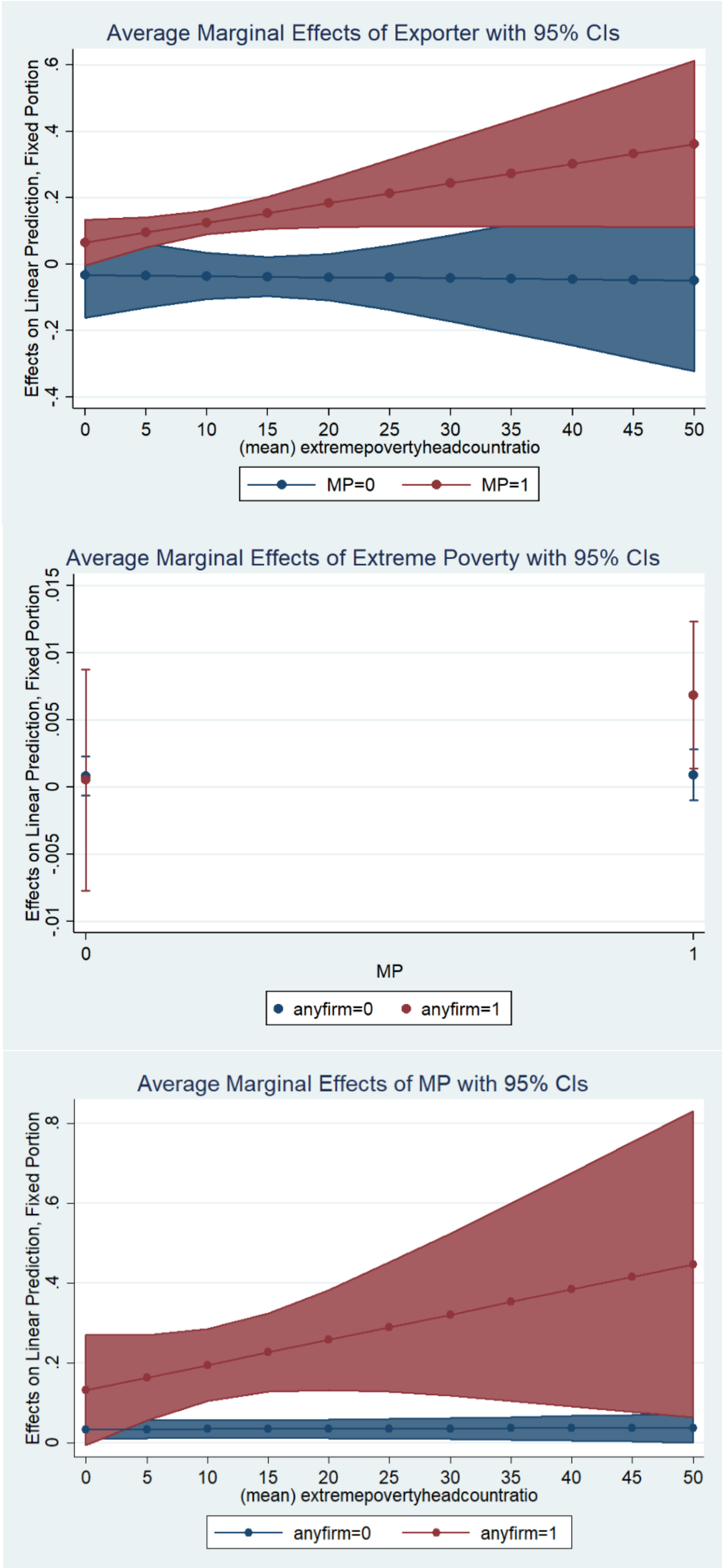


Figure A.8: Three-Way Interactions (All Aid)

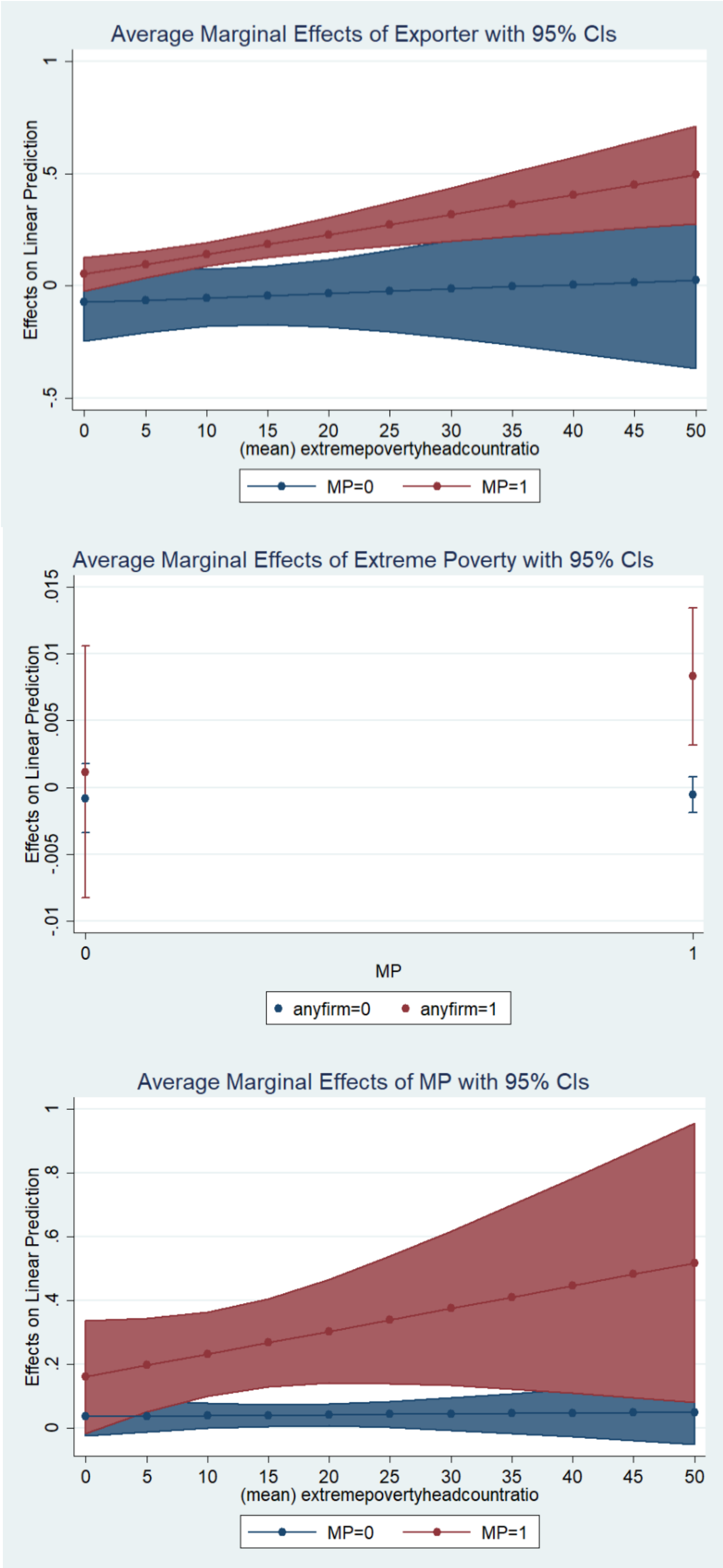


Figure A.9: Three-Way Interactions (Thin AfT)

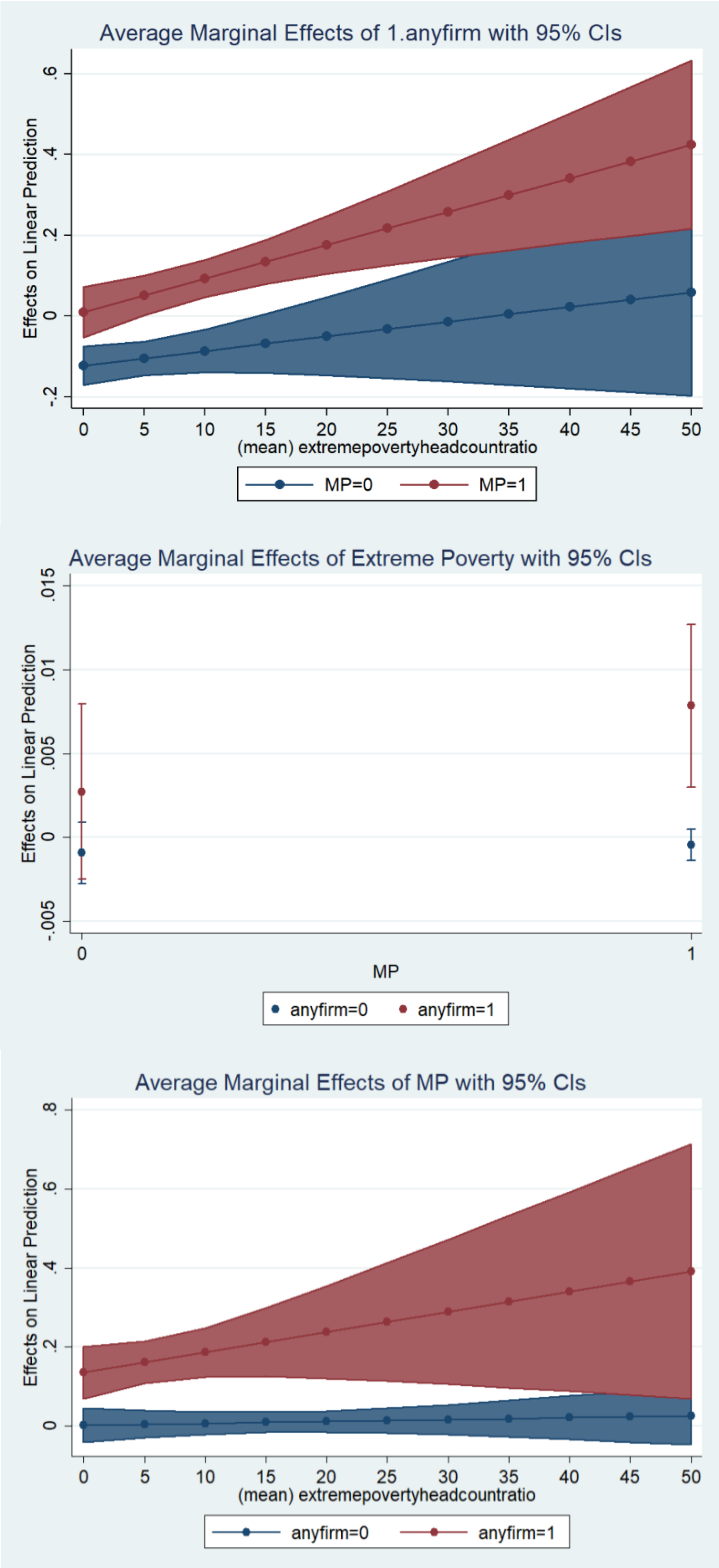


Figure A.10: Three-Way Interactions (Precision Code 2 AfT)

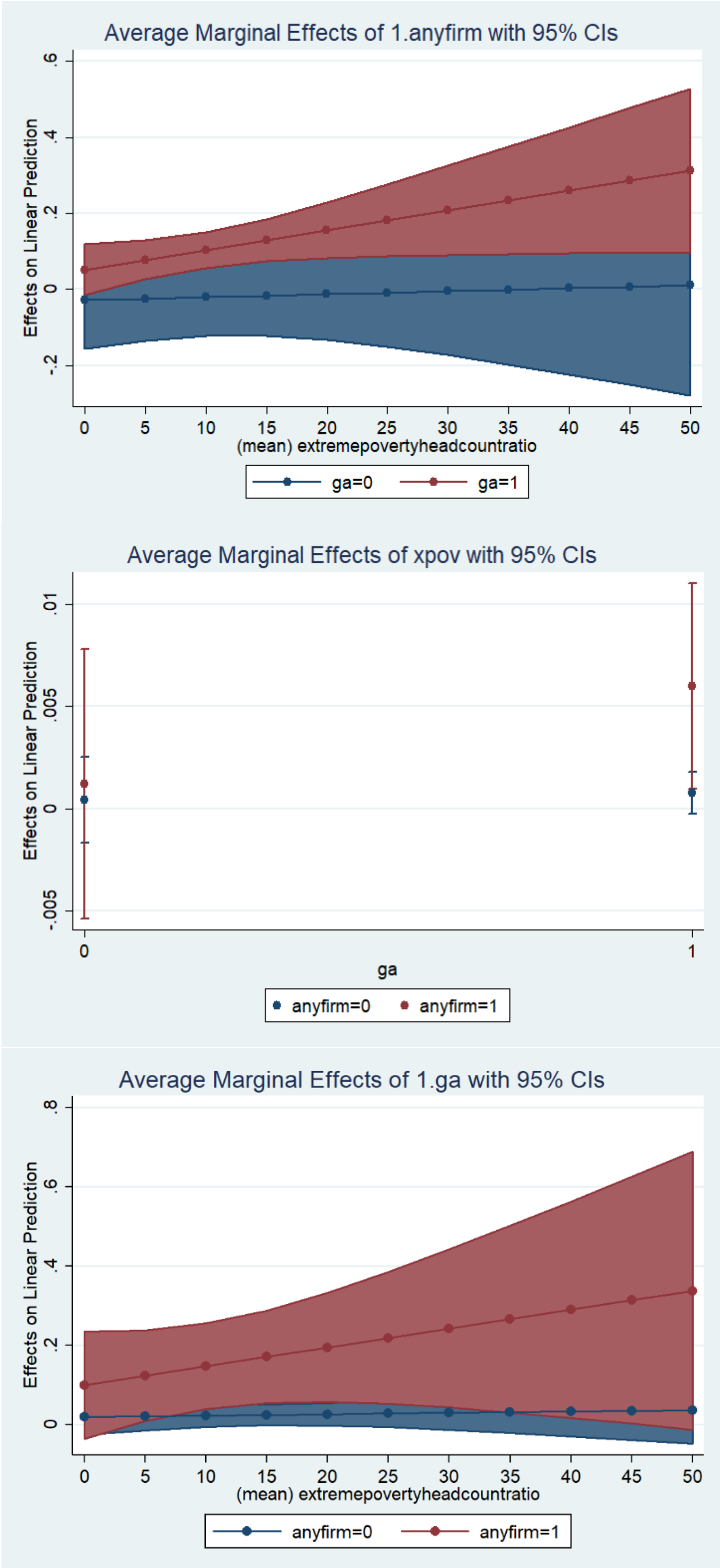


Figure A.11: Three-Way Interactions (Apparel Firms)

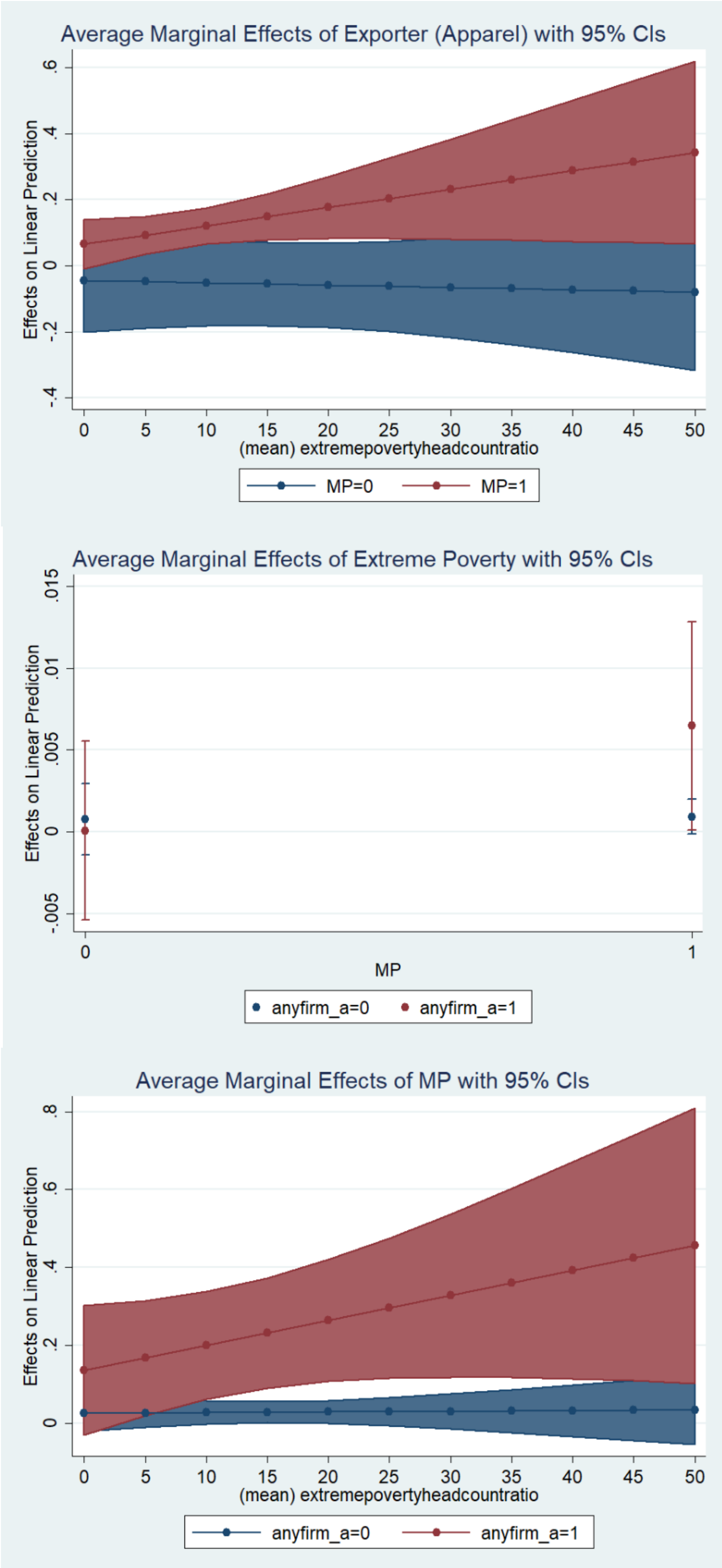
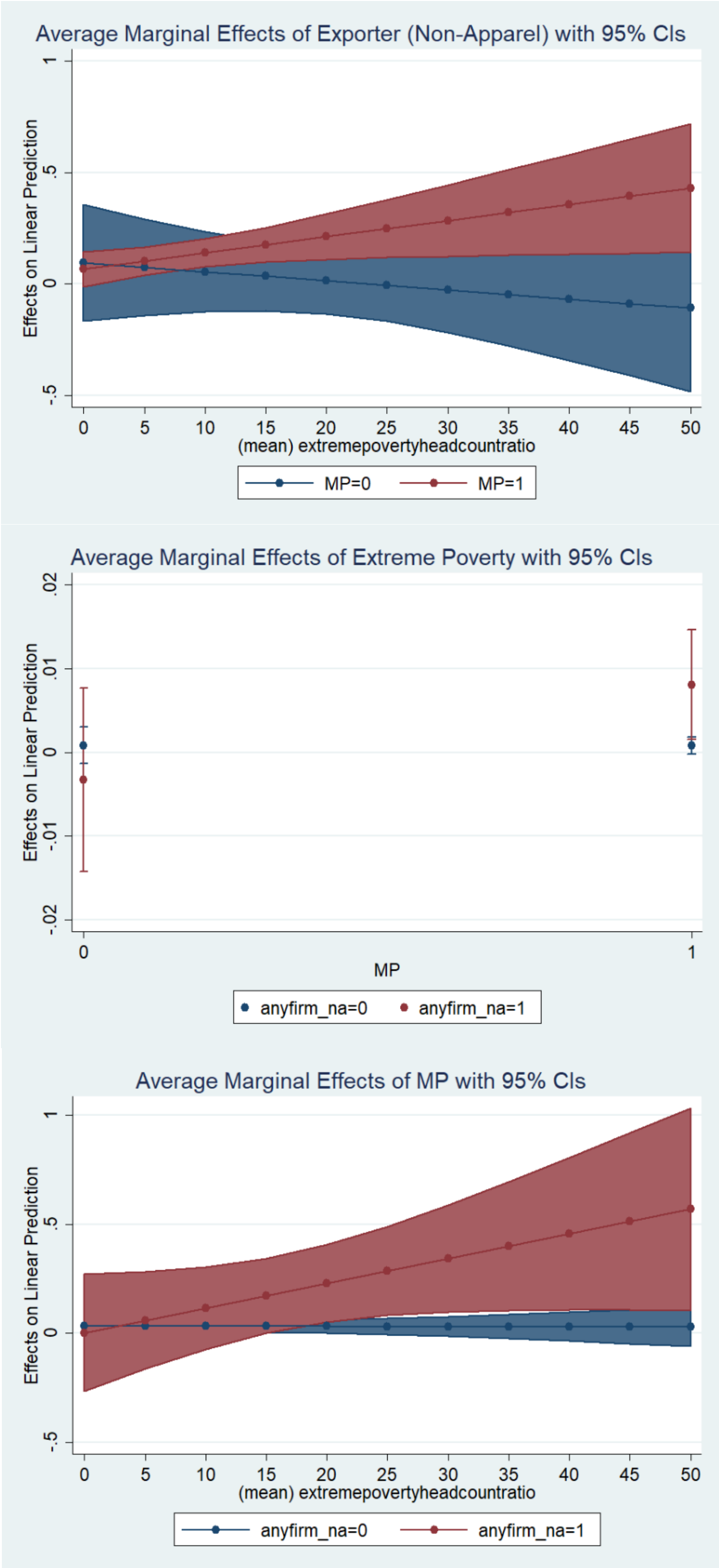


Figure A.12: Three-Way Interactions (Non-Apparel Firms)



AfT Projects

project_id	project_title	donors	aft_thin
32234-023	mff - railway sector investment program (subproject 1)	Asian Development Bank	1
32234-043	railway sector investment program - tranche 2	Asian Development Bank	1
32234-053	railway sector investment program - tranche 3	Asian Development Bank	1
34418-013	southwest area integrated water resources planning and management	Asian Development Bank	1
35049-013	padma multipurpose bridge project	Asian Development Bank	1
35242-013	gas transmission and development project	Asian Development Bank	1
36107-013	sustainable power sector development program (project)	Asian Development Bank	1
36200-013	small and medium-sized enterprise development project	Asian Development Bank	1
36297-013	secondary towns water supply and sanitation	Asian Development Bank	1
37113-013	power system efficiency improvement project	Asian Development Bank	1
38164-013	natural gas access improvement project (formerly clean fuel development project)	Asian Development Bank	1
39295-032	third urban governance and infrastructure improvement (sector) project	Asian Development Bank	1
39298-013	city region development project	Asian Development Bank	1
39405-013	dhaka water supply sector development program (project loan)	Asian Development Bank	1
39408-013	skills development project	Asian Development Bank	1
39432-013	participatory small-scale water resources sector project	Asian Development Bank	1
40515-013	sustainable rural infrastructure improvement project	Asian Development Bank	1
40517-013	public-private infrastructure development facility (ppidf)	Asian Development Bank	1
40540-014	south asia subregional economic cooperation road connectivity project	Asian Development Bank	1
40559-013	second urban governance and infrastructure improvement (sector) project	Asian Development Bank	1
42169-013	greater dhaka sustainable urban transport project	Asian Development Bank	1
42171-013	khulna water supply project	Asian Development Bank	1
42173-013	dhaka environmentally sustainable water supply project	Asian Development Bank	1
42176-012	establishing a regulatory frameworkd for urban water supply and sanitation	Asian Development Bank	1
42180-013	second public-private infrastructure development facility	Asian Development Bank	1
42378-015	power system expansion and efficiency improvement investment program - tranche 1	Asian Development Bank	1
42378-016	power system expansion and efficiency improvement investment program - tranche 2	Asian Development Bank	1

42466-014	skills for employment investment program	Asian Development Bank	1
44142-013	subregional transport project preparatory facility	Asian Development Bank	1
44192-013	bangladesh-india electrical grid interconnection project	Asian Development Bank	1
44192-014	sasec bangladesh-india electrical grid interconnection project (additional financing)	Asian Development Bank	1
44212-012	coastal towns infrastructure improvement project	Asian Development Bank	1
44212-023	coastal towns infrastructure improvement project	Asian Development Bank	1
44305-012	support for climate change mitigation and renewable energy development	Asian Development Bank	1
45078-001	strategic master plan for chittagong port	Asian Development Bank	1
45084-002	coastal climate-resilient infrastructure project	Asian Development Bank	1
45174-001	dhaka-chittagong expressway public-private partnership design project	Asian Development Bank	1
45203-002	natural gas transmission and distribution development investment program	Asian Development Bank	1
45916-012	industrial energy efficiency finance program	Asian Development Bank	1
46452-001	sasec railway connectivity investment program	Asian Development Bank	1
46456-002	supporting education and skills development investment programs	Asian Development Bank	1
46904-014	pran agribusiness project	Asian Development Bank	1
47022-001	supporting participation in the south asia subregional economic cooperation trade facilitation program	Asian Development Bank	1
EU18	cross-border transfer of agricultural technologies, institutional and market development	Delegation of the European Union to Bangladesh	1
EU29	switch-asia, promoting sustainable consumption and production	Delegation of the European Union to Bangladesh	1
EU39	trade policy support programme	Delegation of the European Union to Bangladesh	1
India1	akhaura-agartala rail link project	India	1
India11	feasibility study for gauge conversion of the dhaka-chittagong rail line	India	1
India15	akhaura-agartala rail link project	India	1
India21	akhaura-agartala rail line	India	1
India22	inland river port at ashuganj	India	1
India23	interest equalization support (ies) to exim bank for line of credit extended to bangladesh	India	1
India6	support to handloom promotion	India	1
IsDB5	bangladesh marine fisheries capacity building project (bmfcbp)	Islamic Development Bank	1

JICA1	karnaphuli water supply project (phase 2)	Japan International Cooperation Agency	1
JICA10	khulna water supply project	Japan International Cooperation Agency	1
JICA11	padma multipurpose bridge project	Japan International Cooperation Agency	1
JICA13	chittagong city outer ring road project	Japan International Cooperation Agency	1
JICA14	rural electrification upgradation project	Japan International Cooperation Agency	1
JICA15	south western bangladesh rural development project	Japan International Cooperation Agency	1
JICA3	renewable energy development project	Japan International Cooperation Agency	1
JICA4	the kanchpur, meghna and gumti 2nd bridges construction and existing bridges rehabilitation project (i)	Japan International Cooperation Agency	1
JICA5	bheramara combined cycle power plant development project	Japan International Cooperation Agency	1
JICA7	national power transmission network development project	Japan International Cooperation Agency	1
JICA9	financial sector project for the development of small and medium-sized enterprises	Japan International Cooperation Agency	1
P040712	water management improvement project	World Bank	1
P065131	haripur power project	World Bank	1
P090807	bangladesh - skills and training enhancement project	World Bank	1
P093988	dhaka water supply and sanitation project	World Bank	1
P095965	siddhirganj power project	World Bank	1
P103999	chittagong water supply improvement and sanitation project	World Bank	1
P118605	efficient lighting initiative for bangladesh	World Bank	1
P119547	gpoba: rural electrification & renewable energy	World Bank	1
P120843	bd private sector development	World Bank	1
P120843_1	bd private sector development_PHASE1		1
P122269	bangladesh rural water supply and sanitation project	World Bank	1
P123828	second rural transport improvement project	World Bank	1
P129920	bangladesh: rural electricity transmission and distribution project	World Bank	1
P131263	rural electrification and renewable energy development ii (rered ii) project	World Bank	1
P145118	additional financing: skills and training enhancement project	World Bank	1
P148881	bangladesh trade and transport studies	World Bank	1
P150001	rered ii additional financing	World Bank	1
USAID28	poverty reduction by increasing the competitiveness of enterprises (price)	USAID	1

USAID44	feed the future aquaculture project	USAID	1
USAID47	bangladesh trade facilitation activity (tfa)	USAID	1
USAID49	catalyzing clean energy in bangladesh (cceb)	USAID	1
EU10	inspired-integrated support to poverty and inequalitity reduction through enterprise development	Delegation of the European Union to Bangladesh	0
GB-1-107402	economic empowerment of the poorest	Department for International Development	0
GB-1-203228	underprivileged children's education and skills programme	Department for International Development	0
P098151	clean air and sustainable environment project	World Bank	0
P106135	grameen shakti solar homes project	World Bank	0
P122201	bd: leveraging ict growth, employment and governance project	World Bank	0
P123457	bangladesh integrated agricultural productivity project	World Bank	0
P128276	coastal embankment improvement project - phase i (ceip-i)	World Bank	0
USAID1	accelerating agriculture productivity project improvement (aapi)	USAID	0
USAID41	agricultural value chains (avc) project	USAID	0
USAID48	bangladesh agricultural infrastructure development program (baidp)	USAID	0
USAID7	myap: strengthening household ability to respond to development opportunities	USAID	0

AfT Textual Algorithm

```
replace project_title=lower(project_title)
replace ad_sector_names=lower( ad_sector_names)


*CODING USING AD SECTOR NAMES

*trade

gen ad_trade= strpos(ad_sector_names, "trade") >0

*infrastructure utilities

gen water=strpos(ad_sector_names, "water") >0
gen energy=strpos(ad_sector_names, "energy") >0
gen ad_infra_utility=0
replace ad_infra_utility=1 if water==1 | energy==1

*infrastructure transport
```

```
gen ad_infra_transport =strpos(ad_sector_names, "transport") >0
gen ad_aft=ad_trade + ad_infra_utility+ad_infra_transport

*CODING USING PROJECT TITLES

*trade
gen trade_present_title = strpos(project_title, "trade") > 0
gen export_present_title = strpos(project_title, "export") > 0
gen import_present_title = strpos(project_title, "import") > 0
gen customs_present_title = strpos(project_title, "customs") > 0

gen title_trade=0
replace title_trade=1 if trade_present_title==1 | export_present_title==1 |
import_present_title==1 | customs_present_title==1

*infrastructure_transport
gen road_present_title = strpos(project_title, "road") > 0
gen port_present_title = strpos(project_title, "port") > 0
gen support_present_title = strpos(project_title, "port") > 0
replace port_present_title=0 if support_present_title>0
gen rail_present_title = strpos(project_title, "rail") > 0
gen highway_present_title = strpos(project_title, "highway") > 0
gen bypass = strpos(project_title, "bypass") > 0
gen bypass1 = strpos(project_title, "by-pass") > 0
gen piste = strpos(project_title, "piste") > 0
gen route = strpos(project_title, "route") > 0
gen navigation = strpos(project_title, "naviga") > 0
gen routier = strpos(project_title, "routier") > 0
gen bridge = strpos(project_title, "bridge") > 0

gen infrastructure_transport=0
replace infrastructure_transport=1 if road_present_title==1 | port_present_title==1 |
rail_present_title==1 | highway_present_title==1 | bypass==1 | bypass1==1 | piste==1 |
route==1 | navigation==1 | bypass==1 | routier==1 | bridge==1

*infrastructure_utilities
gen electricity_present_title = strpos(project_title, "lectri") > 0
gen power_present_title = strpos(project_title, "energ") > 0
replace power_present_title=1 if strpos(project_title, "power") > 0
gen water_present_title = strpos(project_title, "water") > 0
gen hydro = strpos(project_title, "hydro") > 0
gen eauet = strpos(project_title, "eau et") > 0
gen deau = strpos(project_title, "d'eau") > 0
gen leau = strpos(project_title, "l'eau") > 0
gen transmission = strpos(project_title, "transmission") > 0
gen sanitary = strpos(project_title, "sanitair") > 0

gen infrastructure_utilities =0
replace infrastructure_utilities =1 if electricity_present_title==1 | power_present_title==1 |
water_present_title==1 | hydro==1 | eauet==1 | deau==1 | leau==1 | transmission==1 |
sanitary==1

*aft industry training
gen manufac_present_title = strpos(project_title, "manufac") > 0
gen production_present_title = strpos(project_title, "product") > 0
```

```
gen vocational_present_title = strpos(project_title, "vocational") > 0
gen vc = strpos(project_title, "value chain") > 0
gen industry = strpos(project_title, "indust") > 0
gen skills = strpos(project_title, "skills") > 0
gen ps = strpos(project_title, "private sector") > 0
gen employment = strpos(project_title, "employment") > 0
gen technique = strpos(project_title, "technique") > 0
gen commercial = strpos(project_title, "commercial") > 0
gen business = strpos(project_title, "business") > 0

gen  aft_industry =0
replace aft_industry =1 if manufac_present_title==1 | production_present_title==1 |
vocational_present_title==1 | vc==1 | industry==1 | skills==1 | ps==1 | employment==1 |
technique==1 | commercial==1 | business==1

gen aft_total= aft_industry + infrastructure_utilities + infrastructure_transport +
ad_infra_utility + ad_infra_transport + ad_trade + title_trade

keep if aft_total>0
```