Aid and Internal Migration in Malawi

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Abstract

This paper uses geographically disaggregated data to investigate the role of aid projects as a *pull factor* for internal migration in Malawi over the period 1998-2008. We explore the link between aid and internal mobility using a PPML estimator and an IV approach based on a gravity model of migration. Controlling for dyadic factors – such as geographical and cultural proximity - as well as for origin-specific characteristics, we find a positive relationship between the number of aid projects in the district of destination and immigration. We also dig deeper into the mechanisms exploring which types of foreign aid shape migration decisions and through which channels. Taken together, our results show that the positive welfare effects of foreign assistance manifest themselves not only through an increase in economic opportunities, but also through improving access to local public services in recipient districts.

Keywords: Foreign Aid, Malawi, Sub-Saharan Africa, Internal Migration

JEL classification: F35, R2, O55

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1 Introduction

Differentials in economic opportunities and in the availability and the quality of public services are typically among the main factors influencing the decision to migrate (Lucas 2015). Migrants tend to move to areas where employment and income opportunities are larger (Harris and Todaro 1970, Young 2013), or in which the supply of public services - such as health care and education - is more abundant and of better quality (e.g. Clark et. al 2003, Gollin et al 2017).

In developing countries, gaps in terms of public services' provision as well as income opportunities across geographical areas are often related to the spatial distribution of foreign aid projects. Especially in poor and fragile contexts, governments have been relying on development aid to provide those social and economic infrastructures that are crucial for local population's subsistence and wellbeing. Indeed, the volume of ODA flows for several least developed countries (e.g. Burundi, Liberia, Malawi) accounts for large shares of gross national income and represents more than those countries can collect through taxes (OECD 2014). Recent studies focusing on geo-localized aid projects show that development aid is positively associated with healthcare quality (e.g. Kotsadam et al 2018, Odokonyero et al. 2018), education outcomes (e.g. De and Becker, 2015; Martorano et al., 2020) and economic growth (e.g. Dreher and Lohmann 2015; Khomba and Trew, 2019).[4]

This paper investigates the role of ODA projects as a *pull factor* for internal migration. We argue that the presence of aid projects, particularly in poor and aid-dependent countries, positively influences both monetary and non-monetary dimensions of wellbeing at local level, which in turn shape the incentives to migrate internally and drive population movements. While several recent studies focused on *international* emigrant flows (e.g. Berthélemy et al. 2009, Lanati and Thiele 2018a, 2018b, Gamso and Yuldashev 2018), the impact of foreign development assistance on *internal* migration remains substantially unexplored. Yet, much of the population movements especially in developing countries occur internally rather than internationally. Globally, 1 in 7 people are internal migrants (UNDP, 2009; UNDESA, 2013), three times as many as international migrants. Furthermore, internal migration is one of the driving forces underlying the rapid demographic change occurring in most developing countries, particularly in Sub-Saharan Africa (Lagakos, 2020). The challenges imposed by rapid urbanization (Henderson and Turner, 2020) call for a better understanding of the factors influencing migration decisions and the role of international donors in shaping the forces driving population movements.

Our work focuses on the case of Malawi, which presents some desirable characteristics for this type of analysis. On the one hand, internal migration in Malawi is far more relevant than international migration among both rural and urban households.[5] In addition, with a population that still predominantly resides in rural areas (Anglewicz, 2019), internal migration represents the main driver

[4] These results corroborate previous empirical research at the macro level based on cross-country analysis, which found a positive impact of aid disaggregated along various lines on a range of economic and social indicators (e.g. Dreher et al 2008, Birchler and Michaelowa, 2016, Mishra and Newhouse 2009, Boom et al 2004, Clemens et al 2011 and Arndt et al 2015).

[5] See for instance FAO (2017) and Gollin et al 2017 (Table 6).

of urbanization in the country.[6] To this matter, recent estimates for Malawi show that internal migrants account for over half of the annual population growth in urban areas (World Bank, 2016). On the other hand, social and economic infrastructures in Malawi are highly dependent on external financial resources. Aid represents approximately 20% of GNI,[7] and is estimated to account for over three quarters of the country's total development expenditures (Khomba and Trew, 2019). This is especially true as far as the provision of social services is concerned. For instance, 81% of the country's total health expenditure come from foreign donors (CHAI, 2015). Recent works by De and Becker (2015) and Dolan (2018) show that subnational aid in the social sectors is related to improvements in the availability of facilities, the quality of services and various health and educational outcomes. In such a context, foreign aid projects are likely to shape the spatial differences in the provision of public services and economic opportunities. Finally, working on Malawi allows to exploit a rich set of data. Data on both geo-localized aid projects at district level and internal migration flows are in fact simultaneously available for the period 1998-2008.

Our empirical analysis grounds on the implementation of a standard gravity model of migration (e.g. Ortega and Peri 2013), where internal bilateral migration flows are a function of the number of completed foreign aid projects at destination. The availability of highly granular data on migration (from the 2008 population census, published by IPUMS) and aid (from the Malawi Aid Management Platform, published by AidData) allows us to construct a district-level (Malawi's second administrative division) bilateral migration matrix, covering yearly district-to-district mobility over the period 1998-2008. Following the literature applying gravity models to migration choices (e.g. Beine and Parsons, 2015, Bertoli and Fernández-Huertas Moraga, 2015), our model employs a Poisson Pseudo-Maximum Likelihood (PPML) estimator. Consistent with the literature, the proposed identification strategy relies on the inclusion of a large set of fixed effects. We include both origin-time and district-pair fixed effects, whose inclusion significantly lowers the risk of model mis-specification, omitted variable bias and allows us: (a) to isolate and properly identify the impact of aid projects as *pull factor* for internal migration while controlling for time invariant district-pair factors – such as geographical as well as cultural proximity – and origin specific characteristics; and (b) to account for the multilateral resistance to migration (Bertoli and Fernández-Huertas Moraga, 2013).[8] Since our identification strategy cannot completely rule out potential endogeneity concerns, we additionally implement an instrumental variable (IV) approach using a two-step strategy along the lines of Eaton and Kortum (2002) and Head and Ries (2008). Following an established methodology in the aid literature (Nunn and Qian, 2014; Chauvet and

[6] Note that although rural-to-urban migration is widespread, rural-rural migration for work, schooling, marriage, or other reasons has been the dominant internal migration stream within much of the region (Anglewicz et al. 2019).

[7] Data comes from the World Bank World Development Indicators and refers to the period 1998-2008.

[8] The preference for such an estimator lies in the correspondence between the theoretical multilateral resistance terms to migration and the estimated fixed effects coefficients, in addition, to the possibility to control for the share of null cross-district migratory flows (which constitute around 20% of our sample).

Ehrhart, 2018; Dreher et al., 2019), we construct an instrument that exploits the exogenous variation in the supply of aid weighted by the probability of each district to be targeted.

Our results reveal a positive impact of foreign aid as a pull factor for internal migration in Malawi. This effect is not only statistically significant, but also economically relevant. More precisely, doubling the number of aid projects in a given district corresponds to a 4.4% increase in the bilateral migration flows towards that district. A simple back-of-the-envelope calculation shows that moving from the sample median (0 projects) to the 90th percentile (5 projects) of the aid distribution, will lead to 30 more migrants per dyad; this roughly corresponds to an additional 930 immigrants per district, which is about 11% of the average number of migrants over our sample period. This result survives to a battery of robustness checks, including one based on an instrumental variable (IV) approach using a two-step strategy along the lines of Eaton and Kortum (2002) and Head and Ries (2008) and an instrument that exploits the exogenous variation in the supply of aid weighted by the probability of each district to be targeted (Nunn and Qian, 2014; Chauvet and Ehrhart, 2018; Dreher et al., 2019).

Next, we show that the positive effect of foreign assistance on internal mobility (a) does not vary significantly between men and women, (b) is stronger for younger cohorts of emigrants, (c) is predominantly driven by aid allocated to social services such as health care and education, rather than to economic infrastructures, and (d) works exclusively as a pull, rather than as a push, factor for migrants.

In the final part of the paper, we try to identify some of the potential channels at work. Provided that migrants' choices are driven by economic opportunities and differentials in the provision of public services (Lagakos, 2020), we check whether aid-recipient districts show improvements in some of the factors that can drive more migration. We show that this is the case as far as Malawi is concerned. Districts that have received more aid are also those experiencing improvements in economic development (proxied by changes in nightlight density), and those displaying larger availability of facilities spanning the provision of social services to the main utilities.

Our paper contributes to the literature in several ways. First, we complement an existing (but rather small) literature on the link between aid and internal migration, which is almost exclusively confined to the impact of *cash transfer* or *credit access* programs (e.g. Ardington 2009, Bryan et. al 2014, Cai 2020). A common pattern that emerges from those studies is that the access to such programs favors internal migration by relaxing household's liquidity constraints in the presence of substantial upfront migration costs. The focus on cash transfer and credit access programs is particularly suitable to investigate the *budget constraint channel* of aid. However, it limits the scope of the analysis to very specific and quantitatively modest types of assistance, specifically designed to relax liquidity-related constraints. By including the provision of other types of aid, our analysis may capture alternative forces driving the decision to migrate, which go beyond the better capacity of would-be-emigrants to finance their moving costs. We thereby complement previous research which shows that the quality of amenities is a rather important determinant of migration decisions (see, for instance, Dustmann and Okatenko, 2014, who look at the role of amenities at the migrant's origin). Relatedly, our results are also consistent with a recent strand of research showing that internal migration in the African context is mostly directed towards those areas (urban and most densely populated) characterized by higher levels of amenities and an higher concentration of public services (Gollin et al. 2017; Henderson et al, 2019; Henderson and Turner, 2020; Lagakos, 2020).

Second, to the best of our knowledge, there are no other works looking at the role of official development assistance as a *pull factor* for internal migration in a developing country. Given the salience in the policy debate around the issue of how to deal with the rising South-North migration following the so-called refugee crises, scholars mostly investigated the controversial role of foreign aid as a *push factor* for international migration.[9]

Finally, the paper constitutes an attempt to explore the potential mechanisms linking aid to internal migration. In particular, we test whether the provision of aid projects in recipient districts is associated to development outcomes that are likely to affect internal migration flows. This links our paper to the recent literature that uses geo-localized level data to evaluate the impact of aid on both economic and social welfare indicators (Dreher & Lohmann, 2015, Kotsadam et al 2018).

The remainder of the paper is structured as follows. In Section 2, we describe the data employed in the empirical analysis and provide some descriptive evidence on the distribution of aid projects across districts and the geography of internal migrant destinations in Malawi and. Section 3 outlines the model and the econometric approach. Section 4 presents and discusses the regression results, while Section 5 digs deeper into the mechanisms through which foreign aid influences migration decisions. Section 6 concludes.

2 Data and Empirical Specification

2.1 Data on Aid Projects

We employ data on the sub-national distribution of foreign aid in Malawi. Data come from AidData; it is based on information taken from the Malawi Aid Management Platform (AMP) at the Malawi Ministry of Finance. The platform includes donor-reported aid information, which has been geo-localized using the UCDP/AidData methodology (see Tierney et al., 2011). The dataset covers aid projects from 30 donors with an estimated value of $5.3 billion, representing roughly 80% of total external assistance to Malawi during the period considered[10]. Overall, the dataset includes 543 projects spanning over 600 different project locations, for a total of 2,523 observations.

The data provides a rich set of information covering the donor, the year in which each project was originally agreed as well as when it was finally completed, the type of project, the amount committed

[9] See for instance Clemens and Postel (2017)

[10] Information on the dataset is available from the following webpage (accessed on Dec 5, 2019): https://www.aiddata.org/data/malawi-release-17-april-2012

and disbursed, and the sectoral code (following both the AMP and the OECD CRS classification systems).

Due to the specific purposes of our analysis, we adjust the original data in two main directions. First, we consider only those projects that have been *completed* by the end of 2008 (i.e. the latest year for which information on internal migration is available). This excludes a large number of projects (around 76% of total), whose expected completion is successive to 2008[11]. Second, we only consider projects whose geographic location is defined with a minimum level of precision making them safe to be associated to a precise district, our spatial unit of interest. The AidData data set provides a precision code for each georeferenced project, indicating the level of granularity of the GPS data. Following the approach of previous studies (e.g. Briggs, 2018; Martorano et al., 2020), we consider projects with a precision code up to 4, meaning that the project location is – in the least granular case – analogous to a first order administrative division such as a province, state or governorate. This further reduces the number of observations by about 18%.[12]

Our final sample includes 65 projects, covering a total of 411 project-locations (see Figure 1). Geographically, the projects are spread over all the districts, with a slight majority being based in the capital area (Lilongwe, accounting for about 10% of the total), and Zomba (8.8%). The vast majority (about 68.9% of the total) of the projects in our sample are provided in the form of grants (the rest being mostly loans, while only two projects are supplied as technical assistance). Concerning the group of donors, multilateral agencies and organizations are the most active (including, in order of importance the African Development Bank, the European Commission, World Bank and FAO). Among the bilateral donors, the most present in Malawi are the US, Norway and Germany.[13] Overall, aid appears to be highly concentrated among few very large donors, with the top seven representing about 90% of the total number of projects.

Figure 1- Location of Aid Projects (1998-2008)

[11] We nonetheless exploit the information on projects that are not yet completed by the end of our sample period (2008) in some robustness checks reported in Section 4.2.

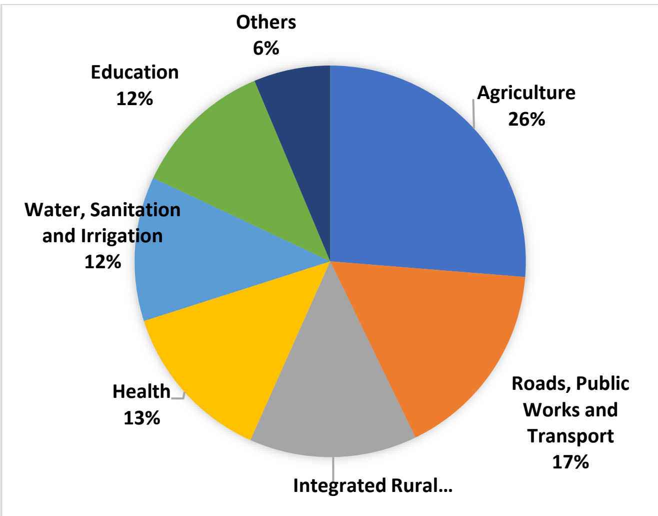
[12] Projects with a precision code higher than 4 are in almost all cases projects that have not been geolocalized at all. These includes for the largest part grants directed to the central government in sectors related to Governance.

[13] Our sample does not include any Chinese aid projects. Malawi only entered into official diplomatic relations with China in 2008. Since then, Malawi started to receive Chinese aid projects on a regular basis.

Notes: The graph includes the location of completed projects concluded in the period 1998-2008, reported with a precision code lower than 5.
Source: Authors' elaboration on AidData.

As far as the sectoral distribution is concerned (Figure 2), most of the projects are concentrated in six groups: agriculture, infrastructures, rural development, health, water and education. Taken together, these sectors account for over 93.7% of the total number of projects. The remaining projects span different – and less well-defined – categories, including gender, governance, vulnerability or risk management.

Figure 2- Sectoral distribution of Aid Projects (1998-2008)



Source: Authors' elaboration on AidData.

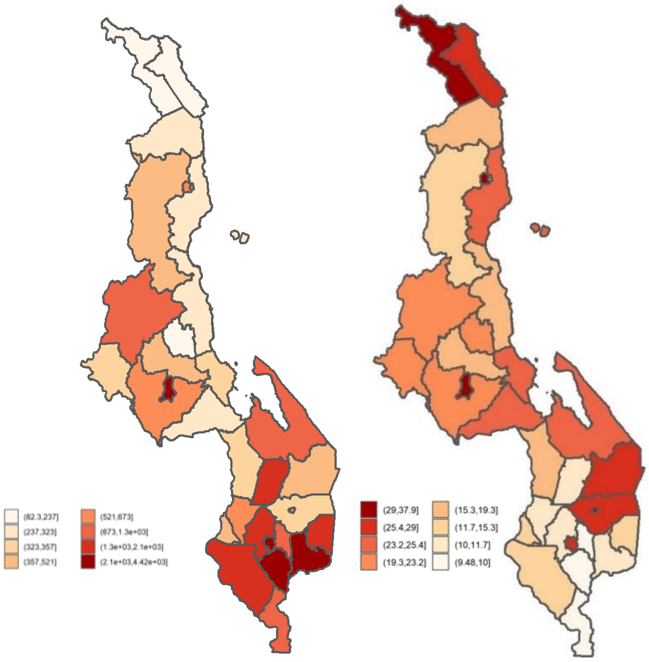
A limitation of AidData is that it is not possible to have precise information on the amount of financial disbursement at the exact project-location level. Since reliable information on the financial disbursement is only available at the overall project level (i.e. as the cumulative disbursement of all project-location entries sharing the same project code), we resort to using the number of projects as our main variable of interest. We still consider financial amounts in some robustness checks, following the related literature and dividing the total financial disbursement of a project by the number of its locations (see for instance, Dreher et al., 2016).

2.2 Migration Data

We employ the 2008 population Census to construct a retrospective panel of sub-national bilateral migration over the period 1998-2008. The census was conducted by the Malawi National Statistical Office (NSO), and it is distributed as Integrated Public Use Microdata Series (IPUMS) by the University of Minnesota. Conducted in 2008, the census was addressed to all Malawi residents, including temporarily absent citizens (for less than 6 months) and foreign citizens with a refugee status. In addition to the standard administrative, demographic, occupational, and socio-economic variables, the 2008 Malawi census includes a section that is suitable to track internal migration. Each individual was asked whether she ever changed residence in the past, the location where she previously lived in, and the time that has passed since the last move. IPUMS data are made available as a "*systematic sample of every 10th household with a random start, drawn by the Minnesota Population Center*" to preserve anonymity of respondents while retaining the representativeness of the data.[14]

Figure 3 – Migration intensity (left) and growth (right) by District

[14] See https://international.ipums.org/international-action/sample_details#mw for additional sampling details.



Notes: Shaded areas (from light to dark) denotes immigration intensity (left panel) and immigration growth (right) by district over the period 1998-2008. Source: Authors' Elaboration based on IPUMS data

Given that the information about the previous residence is only made available at ADMIN2 level, our unit of observation is the district.[15] Starting from the census year 2008, we construct a bilateral migration matrix as the sum of all individuals declaring to have moved to the current district of residence from any other district in a given year[16]. Going backward, we reconstruct the internal migration flows that occurred each year from 1998 to 2008. Formally, this procedure implies that we compute between-districts migration as follows:

$$Mig_{ij,t} = \sum_{p=1}^{n} P_{i,t}[district_{t-1} = j]$$

P denotes each individual currently residing in district $i = 1, \dots, n$, who moved from district $j = 1, \dots, n$ $(with\ i\ \neq j)$ in a given year, accounted for by $t = 1998, \dots, 2008$. About 40% of the total Malawian population in 2008 (i.e., around 5.2 million people) declared to have changed their district of residence at least once over the course of life. Among them, slightly less than 3 million persons have changed their district of residence during our sample period, covering the decade 1998-2008.

[15] The census data track the current place of residence up to the third administrative division of the country (namely, the Traditional Authorities. See for instance Runfola and Napier, 2016). Nonetheless, we cannot go more granular since the IPUMS anonymization procedure allows to track the previous residence of migrants (whose information is needed to build the bilateral migration matrix) at the district level.

[16] Note that by doing this we do not consider internal migration flows due to movements of people *within* district (i.e. from rural to urban areas), which is itself an important component of internal migration (Becerra-Valbuena and Millock, 2020).

The patterns of internal migration display some geographic heterogeneity (see Figure 3, left panel). The districts in the southern region experienced strong inflows of migrants, coming mostly from other districts in both the southern and the central regions. The strong inflows of people in the south can be explained by the presence of large fisheries and fish farms in the southern shore of lake Malawi, as well as to the massive agriculture-targeting national investment policy launched by the national government in the early 2000s, which mostly benefited the districts in the area (Martorano and Cornia, 2017). Still, the areas in the South exhibited the lowest growth rate of immigrants over the period 1998-2008 (Figure 3, right panel). The central region is also an attractive area: however, most of the flows directed to the region are concentrated in the capital city, Lilongwe.

Under a pure demographic perspective, internal migrants in Malawi are distributed equally between men and women (Table A1 in the Appendix). This seems to suggest that even though the triggers of internal mobility in Malawi might differ by gender (Anglewicz et al, 2018; 2019), the two groups have equal propensities to migrate. The average migrant tends to be older by 15 months older than the typical non-migrant (22.6 years of age against 21.3), despite a very low average age at migration –between 8 and 9. Unfortunately, it is impossible to assess with certainty whether children migrate alone or together with their parents. Nonetheless, the very young age at migration (below 3 years old) suggests that at least part of the migrant children move following their parents or other relatives.

The methodology we follow to reconstruct migration data presents three main limitations, which need to be kept in mind for the interpretation of the empirical analysis. First, it does not allow to keep track of any intermediate migration steps that an individual might have undergone between 1998 (the starting period of our panel) and the year in which the last movement is declared. The questionnaire does not aim at mapping the entire migration history of each individual, but it only asks about the last place of previous residence. Given that earlier migration in our sample reduces the probability of previous migratory movements during our period of interest, this issue is likely to matter more for late waves of our panel than for the earlier ones. Second, we can only rely on information about individuals which were alive at the time of the 2008 census. This implies that the migration flows we reconstruct following the strategy discussed above (by not including those individuals who did migrate but did not survive to the census) might eventually be underestimated. This point is more likely to be relevant for earlier waves than for more recent ones[17]. Lastly, Malawi's 2008 census does not distinguish between internally displaced people (IDPs) and voluntary migrants. Given the dynamics of internal migration in Malawi and the incidence of drought in the country across the years (IDMC, 2019), the lack of such information could represent a potential threat to our identification. Nonetheless, our empirical strategy is robust enough to this occurrence, as it focuses on the habitual residence of the respondents (that is, people claiming to have migrated are also asked whether they also permanently changed residence in the period), while the definition of IDPs hinges on the displacement from the place of habitual residence.

[17] In quantitative terms, though, this is unlikely to represent a major concern. Table A2 in the appendix shows that people aged 65 or more look underrepresented.

The latter point is confirmed by the data, which do not exhibit any relevant spike in district-level outflows in the period considered.

2.3 Empirical Specification

Our econometric specification relies on a standard gravity model of migration (e.g. Ortega and Peri 2013) where internal bilateral migration flows from district *i* to district *j* at time *t* are a function of the number of completed foreign aid projects at destination and the bilateral migrant networks. Our baseline specification is:

$$\ln\left(N_{ijt}\right) = \alpha_{ji} + \alpha_{it} + \beta \ln(Aid_{jt}) + \vartheta \ln(Network_{ijt-1}) + e_{ijt} \qquad (1)$$

Aid_{jt}, our variable of interest, measures the (log) number of *completed* aid projects within each destination district *j*. Among the controls, we initially include only the migrant network, which is captured by the pre-determined (one-year lagged) stock of migrants from district *i* living in district *j*.[18] We deem this parsimonious specification as sufficient: while it is potentially prone to omitted variable bias, it has the advantage of including no control variable that could possibly absorb part of the overall aid effect (a similar approach has been followed also by Cattaneo and Peri, 2016; and Beine and Parsons, 2017). A limited number of additional controls is subsequently added to test whether our parameter of interest remains unchanged across different model specifications. These include night-time light intensity, a commonly used proxy for local economic activity (Henderson et al, 2010); the occurrence of conflicts and the extent of climate shocks, measured through the Standardised Precipitation-Evapotranspiration Index (SPEI). To keep the discussion and the reading concise, the coefficients for these additional controls are omitted from all sets of results but the baseline (reported in Table 2). Table 1 reports the descriptive statistics for the main variables included in the empirical exercise.

Table 1: Main Descriptive Statistics

Migration: Bilateral Flows and Stocks						
	N	mean	sd	min	max	Null
Migrant Flows $_{od,t}$	9130	298.05	1703.23	0	65630	22%
Network $_{od}$	9130	4081.39	27995.2	0	535300	1%

Aid (different definitions)					
	N	mean	sd	min	max
Number Concluded Projects $_{d,t}$	9130	1.323	2.43	0	12
Number Agreed Projects $_{d,t}$	9130	4.95	5.84	0	35

[18] The network variable is constructed as the number of migrants who moved from district j to district i before year t (and were still resident in the district in 2008).

Disbursement for Concluded Projects $_{d,t}$	9130	18083.41	46309.76	0	300323.25
Disbursement for Agreed Projects $_{d,t}$	9130	56044.58	72096.82	0	410217.94

Additional Control Variables

	N	mean	Sd	min	Max
Conflict $_{d,t}$	9130	0.36	0.38	0	1
SPEI $_{d,t}$	9130	0.30	0.71	-1.34	1.63
Nightlights $_{d,t}$	9130	3.38	1.16	2.00	8.57

Notes: Descriptive statistics of the main variables included in the baseline specification and in robustness checks. The value of ODA is expressed in constant US $. See Table A3 for the complete list of sources.
Source: Authors' Elaboration based on different datasets.

To identify the effect of foreign aid as a pull factor for internal migration, we expand Equation (1) to include an appropriate set of fixed effects - α_{it} and α_{ji} - which significantly lowers the risk of model mis-specification and, most importantly, allows to control for the multilateral resistance to migration (Bertoli and Fernández-Huertas Moraga, 2013). More precisely, the inclusion of origin-time dummies α_{it} controls for origin specific push factors of internal migration and leads to estimates that are consistent with the assumptions underlying the random utility model (RUM) *a la* Ortega and Peri (2013).[19] Furthermore, the term α_{ji} absorbs all the (asymmetric) time-invariant dyadic determinants of internal emigration – such as cultural proximity and transport costs - and generates a *nest* for each district-pair, which further alleviates estimation problems deriving from the potential cross-sectional dependence of the error term (Bertoli and Fernández-Huertas Moraga, 2015). All specifications include standard errors clustered at the level of the destination district[20].

In line with existing applications of the gravity model of migration (e.g. Beine and Parsons, 2015, Bertoli and Fernández-Huertas Moraga, 2015), we estimate Equation (1) using Poisson Pseudo-Maximum Likelihood (PPML).[21] The choice of using PPML as our preferred estimator is justified by two main considerations. First, the share of zeros in our dependent variable is approximately 22%; this fraction is large enough to introduce distortions in standard log-linear fixed effects models. Second, PPML remains consistent in presence of heteroscedasticity (see Head and Mayer 2015; Santos-Silva and Tenreyro, 2006), and fits well the utility-maximizing behavior of the migrants under different distributional assumptions (Schmidheiny and Brülhart, 2011), let alone the correspondence between the fixed effects estimates and the theoretical multilateral resistance terms.

[19] In such a model, the multilateral resistance term does not vary across destinations *j* except the origin *i* itself (Beine et al 2015)

[20] We show in some robustness checks that the results remain consistent to different clustering strategies of the standard errors (see Section 3.2.2).

[21] Despite using PPML we express Equation (1) in log linear form for simplicity.

3 Results

3.1 Baseline Estimates

Table 2 reports the baseline PPML estimates of Equation (2). We start from our preferred specification (Column 1), and then add progressively other controls, namely *Nightlights* - as a proxy for economic attractiveness at destination (Column 2) – along with the presence of *Conflicts* and the occurrence of weather shocks (*SPEI*) at destination (both in Column 3).

Table 2: Baseline Estimates

	(1)	(2)	(3)
Estimator	PPML	PPML	PPML
Dep. Variable	*Migrant Flows*	*Migrant Flows*	*Migrant Flows*
Log Network (od), t-1	0.342*	0.341*	0.339*
	(0.199)	(0.200)	(0.201)
Number Concluded Projects (d), t	**0.044*** **	**0.044*** **	**0.045*** **
	(0.017)	**(0.017)**	**(0.017)**
Nightlights (d), t		0.049	0.053
		(0.041)	(0.041)
Conflict (d), t			0.016
			(0.018)
SPEI (d), t			0.035
			(0.045)
Observations	9,130	9,130	9,130
% Null	.22	.22	.22
Adj. R2	.96	.96	.96
Pair f.e.	Yes	Yes	Yes
Origin * year f.e.	Yes	Yes	Yes

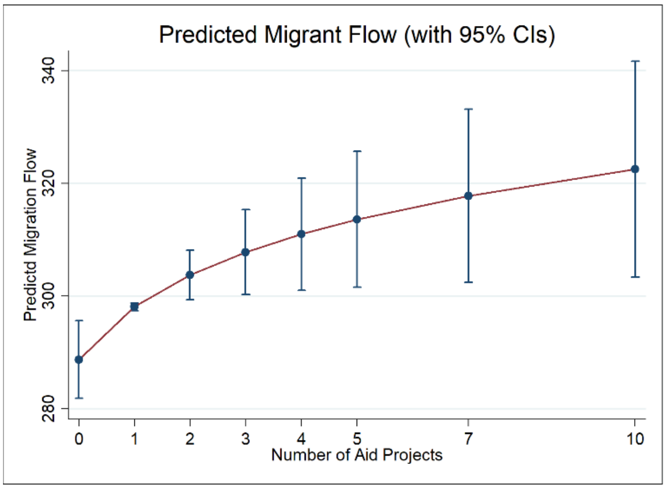
Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors clustered by destination in parentheses. The Table Reports the Results of Equation (1) estimated with PPML with different sets of controls.

The estimates reveal that the number of completed foreign aid projects is positively associated with bilateral migration inflows. In other words, holding other factors constant, an increase in the number of aid projects in a given district over time makes that district more attractive to immigrants. The coefficient of the aid variable is statistically significant and its size remains remarkably stable across the different specifications (Columns 1-3). This implies that the potential effect of aid on the monadic control variables does not substantially bias the coefficient of the number of aid projects in either direction.

The relation that we uncover in the data is not only statistically, but also economically relevant. Our results show that doubling the number of aid projects corresponds to a 4.4% increase in the bilateral migration flows within Malawi. A simple back-of-the-envelope calculation based on predicted flows reported in Figure 4 shows that this implies that a move from the sample median (0 projects) to the 90th percentile (5 projects) of the aid distribution will lead to approximately 30 more migrants per dyad, which means an additional 930 migrants at the level of the destination district. To put these numbers in perspective, this corresponds to about 11% of the average number of migrants per district during the 1998-2008 period.

The network effect always remains statistically significant and with the expected positive sign. Moreover, its elasticity is stable at around 0.3, a coefficient which is in line with previous studies and confirms the role of pre-existing migrant networks as one of the most important factors facilitating migration (see Beine et al 2015).[22]

Figure 4: Quantification



Source: Authors elaboration based on the marginal effect of Aid on bilateral migration. The number of aid projects covers values up to the 99th percentile (10) of their distribution in the estimation sample.

3.2 Robustness

3.2.1 Endogeneity Concerns

An important econometric concern of our specification relates to the potential endogeneity of geo-localized aid projects. The endogeneity of aid allocation may stem from the two canonical channels, i.e. reverse causation and an omitted variable bias. Reverse causation could be an issue if aid increases as a consequence of migration. This would happen, for instance, if specific episodes of migration, e.g. for humanitarian reasons, generate an ad-hoc response by donors. To the best of our knowledge, no such specific events occurred in Malawi during the period analyzed in this paper, and no sudden changes in the provision of humanitarian aid have been recorded in the years 1998-2008.

Omitted variables are possibly the most relevant source of bias in the context of our analysis. Consider for instance those factors related to changes in the political landscape and/or in socio-economic conditions of the districts, which can simultaneously determine migration and aid flows. These factors would imply a correlation between concluded aid projects in district j at time t and the *monadic* component of the error term.

[22] Although it must be noted that the literature we refer to mainly estimates the effect of a network on international (not internal) migration.

This is formally shown in the following equation, which has been obtained by isolating the destination specific component of the error term, ω_{jt}, from equation (1):

$$\ln(N_{ijt}) = \alpha_{ji} + \alpha_{it} + \beta \ln(Aid_{jt}) + \vartheta \ln(Network_{ijt-1}) + (e_{ijt} + \omega_{jt}) \qquad (2)$$

Aid_{jt} might be endogenous because of the potential omission of unobserved factors correlated both with the number of concluded projects in district *j* and the *monadic* component of the error term ω_{jt}. This is particularly compelling in our analysis as - given the constraints in terms of data availability in Malawi - we are able to include only a limited set of district specific controls.

Potential endogeneity is traditionally addressed by means of an instrumental variable (IV) approach. However, the presence of a monadic endogenous variable in a dyadic setting as in Equation (2) makes the IV approach hardly viable in practice, as the instrument should have an *ijt* dimension to qualify. An attractive solution is to implement an instrumental variable (IV) approach using a two-step strategy along the lines of Eaton and Kortum (2002) and Head and Ries (2008).[23] This strategy reduces the second step to:

$$\widehat{\alpha_{\imath t}} = \delta_0 * C_{jt} + \beta \ln Aid_{jt} + \omega_{jt} + \alpha_j + \alpha_t + \epsilon_{jt} \qquad (3)$$

where $\widehat{\alpha_{\imath t}}$ is the estimated destination-year fixed effects, obtained from a first stage structural gravity model $\ln(N_{ijt}) = \alpha_{ji} + \alpha_{it} + \alpha_{jt} + e_{ijt}$. This two-step approach departs from the standard dyadic nature of gravity models as the coefficient of the aid variable in Equation (3) indicates how overall emigration toward a given district is affected by foreign aid. Therefore, the potential endogeneity of our variable of interest can now be addressed in Equation (3) using an instrument that only varies across districts and time (*jt*). Following the existing literature on aid effectiveness (Nunn and Qian, 2014; Chauvet and Ehrhart, 2018; Dreher et al., 2019), we build an instrument that exploits the exogenous variation in the supply of aid weighted by the probability of each district to be targeted. More precisely, we interact a donor-specific time invariant variable - the probability of each district to receive aid from a particular donor *k* in the period considered, $\overline{p_{J,k}}$ – with a time varying district specific variable – the total volume of aid disbursements delivered worldwide but in Malawi, by all donors with at least one project in district *j* at time *t*, $ODA_{k,t}^{(j)}$.[24] Following Dreher et al. (2019), we define the probability of

[23] See Head and Mayer (2015) for a general discussion on the pros and cons for estimating a gravity equation with a monadic variable of interest with a one-step vs two-step strategy.

[24] *K* only excludes FAO and UNIDO for which OECD-DAC does not provide data for the period under scrutiny. These two organizations combined, however, account for a relatively modest 7.4% of the total number of aid projects in Malawi in the period 1998-2008. Hence, we are confident that the exogenous component of the instrument $\sum_k ODA_{k,t}^{K}$ accurately reflects the "*size*" of Donors *k* involved in a specific district *j* of Malawi.

receiving aid from donor k as $\overline{p_{J,k}} = \frac{1}{11}\sum_{t=1}^{11} p_{j,k,t}$. $p_{j,k,t}$ is a binary indicator that is one when district j hosts at least one agreed aid project from donor k at time t. We multiply these two terms and then aggregate over all donors k. The weighted sum computed this way is eventually utilized as an IV at district time level for Aid_{jt}. Such constructed IV is plausibly related to the number of concluded projects under the commonly adopted assumption that an exogenous shock in the total supply of aid should affect the allocation of aid in the same direction (Bartik, 1991). Most importantly, the exclusion restriction should hold, as it is hard to assume that an increase in the total amount of aid spent by donors outside of Malawi should affect internal migration flows in the country. Following the discussion, our first stage then becomes:

$$\ln(Aid_{jt}) = \gamma_1 \left(\sum_k ODA_{k,t}^{(j)} * p_{j,k}\right) + \alpha_j + \alpha_t + \epsilon_{jt} \tag{4}$$

The term γ_1 denotes the correlation of our instrument with the endogenous variable. Since our model is exactly identified, we can only test for the strength of our instrument.

Following existing literature using a similar IV strategy, we can however say something about the potential violation of the exclusion restriction. This is a typical concern in this setting (see, for instance, Goldsmith-Pinkham et al., 2020), which is due to the potential endogeneity of the time invariant component of the instrument (districts with a higher probability of receiving aid can, in fact, be more likely to experience higher inflows of migrants). To show that the latter could not be necessarily an issue of our data, we follow Christian and Barrett (2017) (and Dreher et al., 201XX), and plot the trends of our variables of interest. This provides useful information given that, by construction, the IV exploits the differential effect of changes in in aid provision by the main donors in districts with high- versus those with a low-probability of receiving aid, resembling a difference-in-differences approach whose validity relies on the absence of parallel trends among the two groups of cells (Dreher et al., 2016; Christian and Barrett, 2017). We visually check the trends in the key variables in Figures AX and AX in the Appendix. Districts are grouped into below- and above- average according to the probability of receiving aid. The plots do not show evidence of a violation of the parallel trend assumption in our context. Rather, trends in the groups of recipients look parallel for both the distribution of aid and migration.

Table 3: Two-Step Strategy – IV Method

Model	(1) *Second Step*	(2) *Second Step*
Estimator	PPML	IV-PPML
Dep. Variable	$\widehat{\alpha_{it}}$	$\widehat{\alpha_{it}}$
Number Concluded Projects (d), t	**0.071****	**0.180****
	(0.031)	**(0.074)**
Observations	311	311
Destination FEs	Yes	Yes
Year FEs	Yes	Yes

Kleibergen–Paap F stat	-	26.93
Kleibergen–Paap LM stat	-	6.93
Kleibergen–Paap P-Value	-	.0085
Adj. R2	0.91	0.92

**** p<0.01, ** p<0.05, * p<0.1. Robust Standard errors clustered by destination in parentheses. The Table Reports the Second-Step results of equation (3) estimated with PPML (Column 1) and IV-PPML (Column 2), respectively.*

By combining the first stage with the reduced form results reported in Table A4, we can cautiously conclude that the causal effect of the instrument on the dependent variable runs entirely through the endogenous variable. The Kleibergen-Paap F statistic is above the conventional level and indicates that the instrument is well-identified.[25] The reduced form test supports the exclusion restriction, as it appears that there are no direct effects of the instruments on the dependent variable. The second stage computed using either PPML or IV-PPML (the latter computed with a control function approach as in Dreher et al., 2019) is reported in Table 3.[26]

The point estimate obtained with the 2-step non-IV strategy is not far from the coefficient from our baseline table (Column 1). Once we take account of the endogeneity of the number of projects in our IV regression, the coefficient maintains the same sign and increases when Aid_{jt} is instrumented (Column 2). The IV estimates reinforce our baseline estimates, and point to a causal interpretation of the role of aid projects as *pull factors* for internal migration in Malawi. They also suggest that the results from Table 2 might be interpreted as a lower bound of the effect of aid as a pull factor for internal migration, reflecting measurement issues and other potential sources of bias in the data.

3.2.2: Measurement Issues and Additional Robustness checks

As discussed in Section 2.1, owing to the limitations of the data, counting the number of projects is the most accurate proxy to measure aid effectiveness at the geo-localized level. Yet, we are aware that such an indicator can only imperfectly measure what is going on in the field, as the scale of aid projects is also a very important dimension migration decision might be taken on. Hence, in Table 4 we replicate the estimates of our baseline equation using the total district-level value of concluded projects as variable of interest. The variable is constructed as the sum of all concluded projects financed by donors in a given district at year t. Following other works using AidData (e.g. Dreher et al., 2019; Bluhm et al., 2018), we evenly split the value of each multi-located project across the different sites involved. The impact of aid becomes statistically significant only after accounting for endogeneity using our IV strategy. This result is not surprising given that the value of aid projects is highly prone to measurement error and therefore more subject to endogeneity concerns.

Table 4: Measurement issues (I) – Aid Volume

[25] The F-Test refers to the first stage model estimated with OLS.

[26] According to Wooldridge (2015), the choice of a Control Function approach can be preferable over alternative econometric techniques, as they impose fewer conditions than other methodologies based on maximum likelihood (such as 2SLS) and are computationally simpler than GMM estimators.

	(1)	(2)	(3)
Model	One-Step	2-Step	2-Step
Estimator	PPML	PPML	IV-PPML
Dep. Variable	*Mig. Flows*	$\widehat{\alpha_{1t}}$	$\widehat{\alpha_{1t}}$
Value Aid Disbursements (d),t	**0.003**	**0.005**	**0.056****
	(0.003)	**(0.004)**	**(0.025)**
Log Network (od),t-1	0.362*		
	(0.204)		
Observations	9,130	311	311
District Pair FEs	Yes	No	No
Origin*Year FEs	Yes	No	No
Destination FEs	No	Yes	Yes
Year FEs	No	Yes	Yes
Cragg-Donaldson F stat	-	-	8.004
Kleibergen–Paap LM stat	-	-	4.117
Kleibergen–Paap P-Value	-	-	.0424
Adj. R2	0.91	0.91	0.91

Notes: *** p<0.01, ** p<0.05, * p<0.1 Robust Standard errors clustered by destination in parentheses. Column (1) replicates the results of Equation (1) with the value of Aid disbursement (in log) as main variable. Column (2) reports the effect of aid on the estimated fixed obtained from equation (3). Column (4) reports the second stage IV estimate from equation (3).

In Table 5 we further address some other issues related to the measurement of our variable of interest. First, we consider the possibility that the impact of foreign assistance on bilateral migration at time *t* might be influenced by ongoing projects concluded in past years whose omission could therefore act as confounding factor in our benchmark specification.

Table 5 – Measurement Issues (II) – Different definitions of Aid

	(1)	(2)	(4)
Estimator	PPML	PPML	PPML
Dep. Variable	*Migrant Flows*	*Migrant Flows*	*Migrant Flows*
Log International Network (dist), t-1	0.326	0.318	0.223
	(0.202)	(0.206)	(0.270)
Stock Concluded Projects $_{d,t}$	**0.091*****		
	(0.015)		
Project(s) Concluded in year t		**0.014*****	
		(0.004)	
Number Agreed-and-Incomplete Projects $_{d,t}$			**-0.018**
			(0.015)
Observations	9,130	9,130	9,130
Method	PPML	PPML	PPML
% Null	.22	.22	.19
Adj. R2	.96	.96	.96
Pair f.e.	Yes	Yes	Yes
Origin * year f.e.	Yes	Yes	Yes
VCE	Clustered	Clustered	Clustered
Controls	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1 Robust Standard errors clustered by destination in parentheses. Results refer to Equation (1) estimated via PPML. Different dimensions of Aid are included in the different columns. ***Number Agreed-and-Incomplete Projects*** $_{d,t}$ refers to projects that were agreed but not realized by the end of the last sample year (2008). See table A1 for a detailed description of the variables included

We do this by substituting the number of concluded aid projects at time *t* with the cumulative number of past projects $\sum_{t=1998}^{T} Aid_{j,t}$. Results reported in column (1) show that the coefficient of cumulative aid projects is larger in magnitude with respect to our benchmark result. This finding suggests that ongoing projects concluded in past years have a lasting effect in attracting immigrants. In Column (2) we use a dummy variable instead of the total number of aid projects. Identifying districts according to whether they have received at least one project, without accounting for their number, does not change the substance of our findings. Finally, internal migration does not appear to be influenced by the *future* allocation of aid. In Column (3) we regress district migration on the number of projects that have already been allocated to a district at time t, but were not yet completed by the end of our sample period, i.e. 2008. The lack of a significant effect suggests that the decision to migrate internally is not driven by the promise of future projects at destination, ruling out the possibility of an "anticipation effect" of aid on internal migration.

Last, we check whether our estimates are affected by the composition of the sample, the specification adopted as well as the econometric technique implemented[27]. In a battery of robustness checks, we find that our results hold when we estimate our model using different combinations of fixed effects (i.e. dropping district pair or origin-time effects[28]) or when adopting different clustering strategies of the standard errors (i.e. different types of clustering, such as by origin-destination pairs). We also show that the estimates are not affected by the choice of the estimator. In fact, we get to a consistent set of results when using alternative methods including the EK Tobit (Head and Mayer, 2015) or a simpler OLS with fixed effects model. Finally, we check whether results get confirmed once the top destinations of migration flows are removed from the sample. For instance, dropping the district of Blantyre, the one accounting for the largest shares of both migration flows and stock over time (cf. Figure 3), does not affect the substance of our findings.

4. Heterogeneity and Extensions

4.1 Migrants' characteristics

The results discussed so far point towards a causal effect of aid as a pull factor for human mobility. However, the relation between aid and migration might be heterogeneous across different

[27] All the additional robustness checks described in the rest of the paragraph are not reported in the manuscript for reasons of space, but are available upon request.

[28] Dropping district pair or origin-time fixed effects generally result in an increase in the size of the aid coefficient.

characteristics of the migrants. Gender and age at migration represents two particularly important features, which we explore further in our analysis.

Table A5 in the Appendix reports our results disaggregated by the gender of migrants. As we have seen from the descriptive statistics in Section 2.2, migrants distribute almost equally across gender and our results seem to be consistent with the descriptive statistics. The coefficient of aid is, in fact, positive and statistically significant across the two groups. Also, the magnitude of the coefficient remains very close to our baseline coefficient, though with a slight prevalence of aid-induced migration for males over females. When disaggregating migration flows according to age groups (Table A6 in the Appendix), we find that the impact of aid projects on immigration is predominantly driven by the younger cohorts of the population, which according to our descriptive statistics (see Table A.2) is the one quantitatively more important as far as the period considered is concerned.

4.2 Sectoral Analysis

Various authors (e.g. Clemens et al., 2012; Qian, 2015) argue that the impact of ODA is difficult to interpret as it is comprised of many different types of aid and each type affects a different set of outcomes. Indeed, as reported in Section 2.1, completed aid projects in Malawi span over diverse sectors, including some of the ‘early-impact’ type (Clemens et al., 2012), which can foster internal migration under the promises of short term economic opportunities, as well as other projects, whose attractiveness grounds on the opportunities to access public services not available at the place of origin. To investigate the heterogeneous impact of aid on migration, we group the projects on the basis of their Creditor Report System (CRS) sectoral codes, putting particular attention to distinguish among social and economic sector projects[29]. To account for this, we replicate the same set of regressions of Table 2, but include separate variables for social and economic projects, as well as one additional variable accounting for projects that do not fall in any of these two categories[30]. We include all the sectoral variables in the same model (column 1 of Table 4). Doing this enables us to account for heterogeneous response to different types of aid, complementing the previous analysis on treatment effects. Moreover, it excludes a potential omitted variable bias which might result from the fact that the decision to provide different types of projects is mutually dependent.

[29] The classification follows the recent work by Martorano et al. (2020) on the impact of Chinese aid on household welfare in Africa. The grouping strategy is inspired by the work of Clemens et al (2012), who first identified early-impact aid projects. Economic projects include (CRS code in parenthesis): Transport and Storage (210); Communications (220); Energy Generation and Supply (230); Banking and Financial Services (240); Business and Other Services (250); Agriculture, Forestry and Fishing (310); Industry, Mining, Construction (320); Trade and Tourism (330). Social projects include: Education (110); Health (120); Population Policies (130); Water Supply and Sanitation (140); Government and Civil Society (150); Other Social Infrastructure and Services (160); Women in Development (420); Developmental Food Aid (520); Non-Food Commodity Assistance (530).

[30] This category includes a very small fraction of total projects in our sample (see also Figure 1). Among them, are projects that do not fit into any of the previous categories due to their generic sectoral allocation (e.g., CRS codes 430 “Other Multisector”) or projects that have not been allocated in any CRS code.

Results confirm the main findings of our analysis in that the nexus between aid and migration is confirmed also using sectorally disaggregated aid figures. Moreover, they show that there is indeed some heterogeneity in this relationship. For instance, projects in the social domains have a stronger role in catalyzing internal migration in treated locations. Perhaps surprisingly, we only find limited evidence of economic oriented projects spurring migration at destination. On this respect, it must be noted that most of what is included in the “economic” group is related to the agricultural sector. This is likely to imply that these projects are mostly located in the rural areas of a district, which are less attractive to migrants. Finally, we find a positive and statistically significant effect of unclassified projects. This residual category mostly includes multi-purposed coded projects, the main of which is a $ 21 million project funded by the EU, spanning over 12 different locations in Malawi with the distribution of small projects in different sectors, including health, education, production and community development.

Columns 2-4 of Table 6 reports the results using the sectoral variables separately. There are no changes to the substance of what we found in column 1. An exception is column 3, which shows that – taken alone – economic oriented projects have a significant coefficient.

Table 6: Heterogeneity – Effect of Aid by Destination Sector

	(1)	(2)	(3)	(4)
Estimator	PPML	PPML	PPML	PPML
Dep. Variable	*Migrant Flows*	*Migrant Flows*	*Migrant Flows*	*Migrant Flows*
Log International Network (dist), t-1	0.315	0.331	0.349*	0.337*
	(0.199)	(0.204)	(0.206)	(0.200)
Number Concluded Projects (social) (d), t	**0.055****	**0.072*****		
	(0.021)	**(0.019)**		
Number Concluded Projects (economic) (d), t	**0.004**		**0.031***	
	(0.018)		**(0.018)**	
Number Concluded Projects (else) (d), t	**0.059****			**0.075*****
	(0.023)			**(0.023)**
Observations	9,130	9,130	9,130	9,130
Method	PPML	PPML	PPML	PPML
% Null	.22	.22	.22	.22
Adj. R2	.96	.96	.96	.96
Pair f.e.	Yes	Yes	Yes	Yes
Origin * year f.e.	Yes	Yes	Yes	Yes
VCE	Clustered	Clustered	Clustered	Clustered
Controls	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1 Robust Standard errors clustered by destination in parentheses. Column (1) reports the results from Equation (1) but diversifying the effect of aid between 3 different categories, defined according to CRS coding system. *Economic* projects include CRS codes 210, 220, 230, 240, 250, 310, 320, 330; *Social* projects aggregate CRS categories 110, 120, 130, 140, 150, 160, 420, 520, 530; *Else* contains all the remaining CRS categories that cannot be directly associated to Economic and Social forms of aid. Columns (2) to (4) reports the estimates from Equation (1), but focusing on a single aid sector at a time..

4.3 Aid as a Push Factor

In this last section, we would like to understand whether aid plays uniquely a role as a pull factor, or if it also affects migration choices in the districts of origin. Opposite to what we have studied so far, it could be argued that development assistance can help addressing the root causes of migration through the creation of better opportunities at home, for instance in terms of earnings, higher quality education and better public services. Given the emotional and social cost of migration, such opportunities could give instead people an incentive to stay at home rather than to migrate. Recent empirical research focusing on international emigration collected some evidence in favor of this latter hypothesis, although the resulting impact of aid is rather small (i.e. it would take an unrealistically large increase of foreign assistance to significantly curb migration from developing countries. See for instance Lanati and Thiele 2018a; 2018b).

Table 8: Aid as a Push Factor

	(1)	(2)
Estimators	PPML	IVPPML
Dep. Variable	*Internal Migrant Flows*	
Number Concluded Projects (o), t	**0.023**	**-0.006**
	(0.027)	**(0.004)**
Observations	9,130	311
% Null	.22	.22
Adj. R2	.96	-
District Pair f.e.	Yes	Yes
Destination*Year f.e.	Yes	Yes
District f.e.	No	No
Year f.e.	No	No
Controls	Yes	Yes
Cragg–Donald F stat	-	26.797
Kleibergen–Paap LM stat	-	6.89
Kleibergen–Paap P-Value	-	0.008

Notes: *** p<0.01, ** p<0.05, * p<0.1 ; Robust Standard errors clustered by district of origin in parentheses. The estimates show the effect of the number of concluded aid projects at the origin on bilateral emigrant flows over the years 1998-2008.

To correctly identify the impact of aid projects as a push factor we modify our baseline gravity equation and include now destination-year fixed effects, to capture the potential impact of Aid as a *push factor* of internal emigration in Malawi. We also provide the corresponding IV estimate, obtained by applying the same instrument utilized in Tables 3 and 4. Results are reported in Table 8. The estimates point toward a null impact of ODA on district-level emigration: an increase in the number of aid projects at district level is associated with no statistically significant evidence on variation in the emigration rates. This evidence suggests that while the welfare enhancing effect of concluded aid projects in Malawi influences the relative attractiveness of migrant destinations, it doesn't seem to affect the decision of whether or not to emigrate from places that receive aid. In other words, this result reinforces the view that aid plays a role as a pull, rather than a push, factor to explain the patterns of internal migration in Malawi over the period of our analysis.

5. Transmission channels

So far, we provided extensive and robust evidence on the positive relationship between aid and internal migration in Malawi. In this section, we try to dig deeper into some of the potential channels through which foreign aid can affect internal migration. In light of this, we test empirically two potential mechanisms through which aid can affect internal migration. This includes the capacity of aid to expand local economic opportunities on the one side, and its role as a source of public services and other amenities on the other.

5.1 Economic Opportunities

A first mechanism that we propose to substantiate our findings is linked to the capacity of aid to affect economic growth in targeted districts. To the extent that migration is motivated by the search of economic opportunities, the potential of aid to catalyze internal migration partly grounds on its capacity to spur economic growth. Even though the literature on the aid-growth nexus has been largely inconclusive (see Arndt et al. 2010), most recent evidence exploiting (as we do) more precise information on the sub-national distribution of aid project tends to provide somewhat more positive evidence. This is also true for the case of Malawi. A recent empirical work by Khomba and Trew (2019), which uses the same data that we use[31], shows that economic growth is positively affected by aid flows received by Malawian districts. Importantly, Khomba and Trew (2019) argue that – representing more than 70% of overall development spending– aid is likely to be a major instrument to leverage economic growth in the country.

In Table 7 we run a simple exercise and regress aid projects against the growth rate of nighttime light (NTL) density, a proxy for the growth of economic activity largely used in the literature (see Henderson et al., 2010). The regression includes district and year fixed effects, with standard errors clustered at the district level. In line with Khomba and Trew (2019), results show that receiving aid projects is positively related to economic growth. This finding confirms that aid affects migration choices also through the canonical channel of creating economic opportunities at destination.

5.2 Public Services Provision

Next, we look at the capacity of aid to provide some specific types of public services, including health facilities, schools, or access to basic infrastructures, that can affect the decision to migrate internally (see Dustmann and Okatenko, 2014 and Gollin et al., 2017).

[31] Khomba and Trew (2019) explore the aid and growth nexus for a sample covering Malawian districts over the period 2000-2013. Economic growth is proxied by changes in nighttime light density, and causality is supported by an instrumental variable strategy exploiting co-ethnicity and political support to the President.

To address this question empirically, we employ individual data from rounds 3 and 4 of the Afrobarometer Survey. The Afrobarometer collects geocoded information[32] on people's attitudes about the political, social, and economic condition in their country of residence. Crucially for our purposes, individuals are also asked about the availability and proximity of certain public goods. For Malawi, the survey covers a total of 2,384 individuals based in 68 and 69 clusters in the years 2005 and 2008 respectively.[33]

For our exercise, we exploit a question asking whether a given facility is "…present in the primary sampling unit/enumeration area, or within easy walking distance". We focus on the following facilities: *Schools*, *Health Clinics*, *Electricity*, *Piped Water* and *Sewage System.*

Our analysis links individuals' responses to the above questions to the cumulate number of aid projects received in the district in which each individual is based by the year of the surveys (2005 and 2008). All regressions include individual characteristics (gender, age, residence in rural/urban areas) as well as district and time fixed effects.[34] Table 7 summarizes the findings of this exercise, showing that the probability for an individual to live in proximity of some key facilities is generally higher in locations that have been targeted by foreign aid.

Table 7: Mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	*Avg. Nightlight*					
Dep. Variable	*growth*	*School*	*Clinic*	*Electricity*	*Pipes*	*Sewer*
Mechanism	*Growth*	*Public services*				
Number Concluded Projects $_{d, t}$	**0.001*****					
	(0.000)					
Stock Concluded Projects $_{d,t}$		**0.116*****	**-0.034**	**-0.021**	**0.134*****	**0.125*****
		(0.037)	**(0.046)**	**(0.047)**	**(0.040)**	**(0.039)**
Observations	308	2,209	2,209	2,209	2,209	2,209
R-squared	0.018	0.895	0.466	0.519	0.525	0.414
Controls	Yes	Yes	Yes	Yes	Yes	Yes
District f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1 Robust Standard errors clustered by destination in parentheses.. The dependent variable in column (1) is the yearly average nightlight intensity growth, obtained from NOAA. Columns (2) to (6) are estimated using a Linear Probability Model computed on the sample of respondents from the Afrobarometer survey (Rounds 3 and 4). The dependent variable in each column takes the value of 1 if the related infrastructure (School, Health Clinic, access to Electricity Grid, Piped Water and Sewage System) is located within easy walking distance or if the respondent has easy access to them. All equations include district and time fixed effects. Column (1) include our usual set of district level controls (Population density, SPEI, conflict). Columns (2) to (6) are based on individual responses reported by Afrobarometer,

[32] Enumerator areas for each Afrobarometer survey location have been geocoded by the Aiddata team and are therefore fully comparable to the aid data (Ben Yishay et al., 2017).

[33] Afrobarometer follows a random selection process designed to generate a representative cross section of the population of voting age in each country. The sampling is based on geographic primary sampling units that form the Enumeration Areas, or EA. Such units are selected with a probability proportional to their population size. A respondent is then randomly selected within a randomly selected household within each EA. Gender balance in the sample is controlled by alternating men and women in consequent interviews. For reasons of logistics and budget, each primary sampling unit include 8 interviews.

[34] Note that despite the first and second round of the survey were also overlapping with our period of interest, we could not use them due to the absence of the relevant questions in the previous questionnaires.

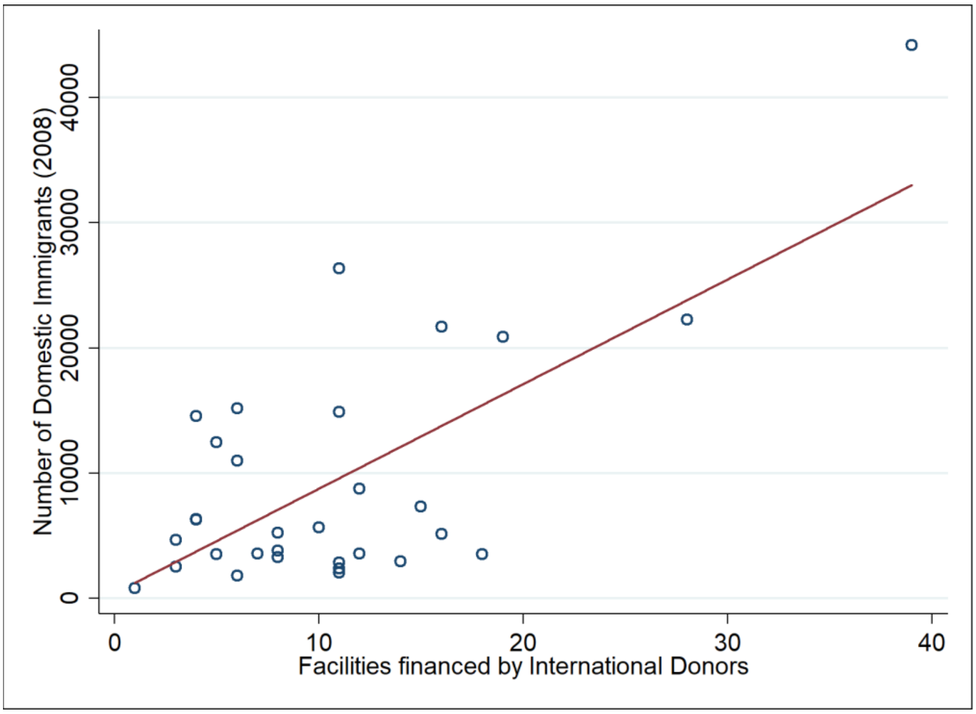
and include a set of individual characteristics (gender, age, rural/urban location), and are weighted using the sample weights (also provided by Afrobaromete) .

The lack of a significant correlation between aid and the availability of health facilities is perhaps surprising, also in view of existing evidence from Malawi (De and Becker, 2015). To further examine this important aspect, we run a descriptive exercise employing the Service Provision Assessment (SPA) survey of the DHS-VI phase, conducted between 2013 and 2014.

SPA surveys collect data on the type and the quality of the services provided at the level of each single geo-localized health facility.[35] We use this information to measure the distribution of health facilities across districts. Importantly, SPA provides details on the number of facilities whose functioning is directly funded by international donors. We correlate this information with the data on the distribution of migration across districts (note that this information does not overlap completely, since migration data stops earlier than the SPA survey). Given the cross-sectional dimension of the data, and the very limited number of observations (N=31), we can only establish correlations on the basis of a visual inspection of the data. Figure 5 reports a graph plotting the number of facilities run by donors with the stock of migrants up to 2008.

Figure 5. Aid-financed health facilities and migration at the district level

[35] Despite the name, SPA surveys collect information on all the health facilities actively operating in a given moment on the national territory.



Note:Source: IPUMS and DHS-SPA survey (2013). The x-axis reports the number of facilities in each of the 31 districts, and that are reported to having been financed by international donors.

6. CONCLUSIONS

The policy and academic debate around the relationship between foreign aid and migration has almost exclusively been centered around the potential role of foreign assistance as an instrument to manage (and curb) international emigration from developing countries. Yet, from a developing country perspective, international migration accounts for a relatively small share of total population movements, as it is characterized by substantive upfront moving costs. Therefore, especially in poor and deprived contexts, internal emigration decisions – namely *whether or not* and *where to* emigrate - are likely to be more sensitive to the welfare enhancing effects of foreign assistance. In this paper, we have analyzed the role of ODA projects as a *pull factor* for within country migration in Malawi. Several insights emerge from our empirical analysis that contribute to the existing literature in many respects.

First, our findings suggest not only that the effect of the number of projects on immigration at district level is statistically significant, but also that the estimated impact is numerically and economically relevant. Taking our point estimates at face value, moving from 0 to 5 aid projects roughly corresponds to an additional 930 immigrants per district, which is about 11% of the average number of migrants per district over our sample period.

Second, our estimates reveal that the positive welfare effects of foreign assistance driving internal immigration manifest themselves either through an improved quality of local public services as well as via an increase in economic opportunities in recipient districts. From a conceptual point of view, this result corroborates previous research on the impact of non-monetary dimensions of well-being as a determinant of the decision to migrate.

Finally, from a policy point of view our results highlight a so far partially unexplored dimension of foreign aid, i.e. its capacity to drive internal migration by affecting the spatial equilibrium in the distribution of economic activities and the provision of public services in less developed countries.

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APPENDIX

Table A1 – Description of Variables and Data Sources

Variable Name	Description	Source
Number Concluded Projects $_{d,t}$	*Number of concluded Aid Projects in district d in year t (in logs)*	AidData
Number Concluded Projects $_{d,t-1}$	*Number of concluded Aid Projects in district d in year t-1 (in logs)*	AidData
Stock Concluded Projects $_{d,t}$	*Number of concluded Aid Projects in district d from t= 0 to t (in logs)*	AidData
Stock Concluded Projects $_{d,t-1}$	*Number of concluded Aid Projects in district d from t= 0 to t-1 (in logs)*	AidData
Value Aid Disbursements (Constant $) $_{d,t}$	*Total disbursement spent for concluded Aid Projects in district d in year t (in logs)*	AidData
Project(s) Concluded in year t	*1 if a project as ever been concluded in district d at time t (dummy)*	AidData
Number Agreed Projects $_{d,t}$	*Number of Allocated Aid Projects in district d in year t which have been completed by 2008 (in logs)*	AidData
Number Agreed-and-Incomplete Projects $_{d,t}$	*Number of Aid Projects in district d allocated in year t but completed after 2008 (in logs)*	AidData
Number Concluded Social Projects $_{d,t}$	*Number of concluded Social-related Aid Projects in district d in year t-1 (in logs)*	AidData
Number Concluded Economic Projects $_{d,t}$	*Number of concluded Economic-related Aid Projects in district d in year t-1 (in logs)*	AidData
Number Concluded Miscellaneous Projects $_{d,t}$	*Number of concluded Non-Social, Non-Economic related Aid Projects in district d in year t-1 (in logs)*	AidData
Value Aid Disbursements (Social) (Constant $) $_{d,t}$	*Total disbursement spent for concluded Social Aid Projects in district d in year t (in logs)*	AidData
Value Aid Disbursements (Economic) (Constant $) $_{d,t}$	*Total disbursement spent for concluded Economic Aid Projects in district d in year t (in logs)*	AidData
Value Aid Disbursements (Miscellaneous) (Constant $) $_{d,t}$	*Total disbursement spent for concluded Non-Social, Non-Economic Aid Projects in district d in year t (in logs)*	AidData
Network $_{od,t-1}$	*Stock of Migrants born in district o and living in district d as in year t-1 (in logs)*	IPUMS
Migrant Flows	*Total number of people that moved from district o to district d in year t (in logs)*	IPUMS-I
Migrant Flows (Men)	*Total number of men that moved from district o to district d in year t (in logs)*	IPUMS-I
Migrant Flows (Women)	*Total number of women that moved from district o to district d in year t (in logs)*	IPUMS-I
Migrant Flows (Young Age)	*Total number of kids (0-14) that moved from district o to district d in year t (in logs)*	IPUMS-I
Migrant Flows (Working Age)	*Total number of workers (15-54) that moved from district o to district d in year t (in logs)*	IPUMS-I
Migrant Flows (Old Age)	*Total number of elders (55+) that moved from district o to district d in year t (in logs)*	IPUMS-I
IV	*Sum of total spending (concluded projects) by each donor operating in district d, weighted by the probability of each donor to be involved in district d over the period 1998-2008.*	AidData
Nightlights $_{d,t}$	*Nighlight Luminescence at destination d district level at time t (between 0 and 1)*	NOAA-DMSP
Conflict $_{d,t}$	*Presence of any form of conflict ad destination district d level (dummy)*	Harari and La Ferrara (RESTAT 2019)
SPEI $_{d,t}$	*Crop affecting natural disasters at destination district d level.*	Harari and La Ferrara (RESTAT 2019)

Notes: Subscripts - o indicates the district of origin; d refers to the district of destination (when referring to internal migration); t refers to time. All variables taken from Harari and La Ferrara (2019) were originally available at cell level, and have been processed and rescaled to match the boundaries of each district.

Table A2: Validity of the Instrument

	(1)	(2)	(3)
Model	Reduced Form	1st Stage	1st Stage
Estimator	PPML	PPML	PPML
Dep. Variable	*Mig. Flows*	*Number Concluded Projects (d), t*	*Value Aid Disbursement (d), t*
Instrument (d),t	0.097	0.786***	3.335***
	(0.103)	(0.195)	(1.217)
Observations	304	304	304
Destination FEs	Yes	Yes	Yes
Year FEs	Yes-	Yes	Yes
Kleibergen–Paap F stat	-	15.6	7.246
Kleibergen–Paap LM stat	-	6.039	3.974
Kleibergen–Paap P-Value		.014	.0462

Table A3 - Composition of Migration (total # of people) - Age groups by year

Year Migrated	**Children**	**Working age**	**Elderly**	**Total**
1998	105,100	70,160	2,050	177,310
1999	93,770	44,480	1,320	139,570
2000	125,880	70,250	1,750	197,880
2001	129,580	62,220	1,700	193,500
2002	125,750	64,230	1,670	191,650
2003	156,730	91,480	2,200	250,410
2004	174,000	96,750	2,010	272,760
2005	192,710	111,450	1,720	305,880
2006	201,360	125,800	1,840	329,000
2007	204,930	114,470	1,690	321,090
2008	297,130	218,790	3,560	519,480

Notes: Migrants flows distribution by age group and year of migration. Children refers to migrants less than 18 years old. Working age include people between 18 and 54. Elderly includes all migrants older than 54.
Source: Authors' elaboration based on Malawi 2008 Census (IPUMS).

Table A4 - Composition of Migration (total # of people) by Gender

	1998				2008			
	Women		Men		Women		Men	
District	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
Blantyre City	10210	102060	11830	108100	52080	309540	54690	320140
Lilongwe City	5490	32680	6310	38360	25420	134160	26560	147750
Thyolo	8680	182460	8950	155190	18870	305000	18850	278780
Mulanje	7600	170290	7710	141770	15380	270910	14970	242820
Chikwawa	7600	118380	7430	118650	15070	215910	15180	215100
Blantyre	5490	101180	5340	91900	11100	170670	10740	160360
Balaka	5460	88710	4970	75550	10820	159230	10630	146220
Phalombe	4910	94030	4790	79920	10090	162810	9720	147290
Chiradzulu	4430	93170	4700	76320	8660	150620	7950	134260
Mangochi	2290	22240	2190	20590	8070	56570	8150	55250
Kasungu	2510	25150	2970	27690	7300	65260	7540	69580
Zomba City	1300	10000	1490	10690	7260	39880	7510	41560
Nsanje	3670	65840	4240	64810	7400	117710	7200	115220
Mzuzu	1710	8220	1580	8470	7300	38310	6800	38030
Lilongwe	1020	12260	1070	12900	6050	39380	6630	40350
Mzimba	1400	13100	1330	13610	4330	37690	4680	37890
Mwanza	1200	24100	1450	21600	4340	46090	4440	43690
Machinga	890	9890	1030	9220	3980	27980	4160	27560
Neno	1910	29860	1800	26870	3560	54330	3530	51370
Ntcheu	840	11150	1040	10840	3350	27570	3540	27710
Salima	820	9110	840	9920	3210	24110	3530	26330
Zomba	1130	10830	1070	11590	3470	27350	3120	28550
Mchinji	1080	10940	1160	12510	3270	27150	2980	29440
Dowa	1150	11780	880	11540	3000	29180	3000	27830
NkhataBay-Likoma	620	4530	650	5220	2610	16060	3250	17950
Dedza	660	6420	730	6470	2560	19450	2790	20690
NkhotaKota	820	10110	1010	12230	2360	23560	2470	26860
Karonga	380	4380	350	3900	2280	14710	2180	13440
Rumphi	720	5400	730	5480	2150	16650	2190	16910
Ntchisi	610	5980	550	6090	1730	14470	1630	14520
Chitipa	230	1910	290	1780	830	5780	970	5620

Source: Authors' elaboration based on Malawi 2008 Census (IPUMS).

Table A5 – Heterogeneity (I): Effect of Aid by Gender.

	(1)	(2)	(3)
Estimator	PPML	PPML	PPML
Dep. Variable	*Migrant Flows (all)*	*Migrant Flows (men)*	*Migrant Flows (women)*
Log Network (od), t-1	0.339*	0.287	0.392*
	(0.201)	(0.191)	(0.213)
Number Concluded Projects (d), t	**0.045*** **	**0.050** **	**0.040*** **
	(0.017)	**(0.023)**	**(0.014)**
Observations	9,130	9,040	8,880
% Null	.22	.22	.2
Adj. R2	.96	.94	.94
Pair f.e.	Yes	Yes	Yes
Origin * year f.e.	Yes	Yes	Yes
VCE	Clustered	Clustered	Clustered
Controls	Yes	Yes	Yes

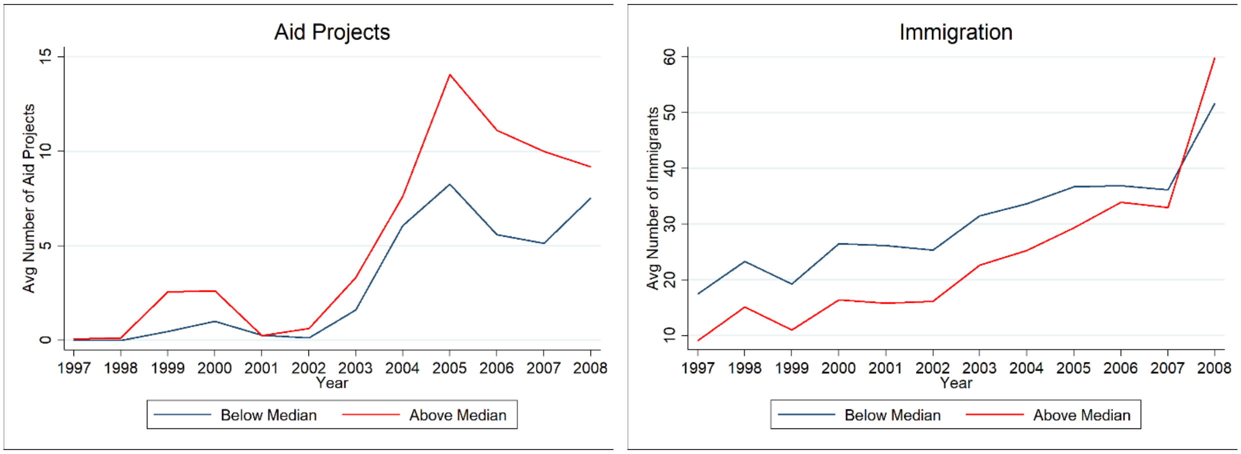
*Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ Robust Standard errors clustered by destination in parentheses. Column (1) reports the estimates from Equation (1) computed on total migration flows. Column (2) and (3) reports respectively the estimates for Men and Women taken separately.*

Table A6: Heterogeneity (II) – Effect of Aid by Age of Migrants

	(1)	(2)	(3)	(4)
Estimator	PPML	PPML	PPML	PPML
Dep. Variable	*Migrant Flows*	*Migrant Flows*	*Migrant Flows*	*Migrant Flows*
	All	**Youth**	**Work_Age**	**Old_Age**
Log Network (od), t-1	0.339*	0.277	-0.396***	-4.968***
	(0.201)	(0.186)	(0.086)	(0.939)
Number Concluded Projects (d), t	**0.045*** **	**0.066** **	**0.028**	**0.024**
	(0.017)	**(0.026)**	**(0.024)**	**(0.106)**
Observations	9,130	8,750	9,110	4,245
Method	PPML	PPML	PPML	PPML
% Null	.22	.35	.26	.74
Adj. R2	.96	.97	.88	.4
Pair f.e.	Yes	Yes	Yes	Yes
Origin * year f.e.	Yes	Yes	Yes	Yes
VCE	Cluster	Cluster	Cluster	Cluster
Controls	Yes	Yes	Yes	Yes

*Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ Robust Standard errors clustered by destination in parentheses. Column (1) reports the estimates from Equation (1) computed on total migration flows. Column (2), (3) and (4) reports the estimates for young migrants (less than 16y.o), Working Age population (between 16 and 64 years of age), and Old age migrants (more than 64 y.o) respectively.*

Figure A1: Parallel Trends



Parallel trends in average number of aid projects (left) and average number of immigrants (right) between country with above and below median probability of receiving aid over the period of interest..