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Expansion of Djibouti's National Family Solidarity Program: Understanding Targeting Performance of the Updated Proxy Means Test Formula

Vibhuti Mendiratta, Amr Moubarak,
Gabriel Lara Ibarra, John van Dyck,
and Marco Santacroce



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1818 H Street NW
Washington DC 20433
Telephone: +1 (202) 473 1000
Internet: www.worldbank.org

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Expansion of Djibouti's National Family Solidarity Program: Understanding Targeting Performance of the Updated Proxy Means Test Formula

Vibhuti Mendiratta, Amr Moubarak, Gabriel Lara Ibarra, John van Dyck and Marco Santacroce¹

Abstract

Djibouti, a low-middle income country at the horn of Africa, is undertaking commendable efforts to combat extreme poverty and early childhood development challenges faced over the past few decades which has been exacerbated by the series of droughts facing countries in the horn of Africa coupled with significant increases in costs of fuel and food since early 2000s. A key pillar of Djibouti's poverty and human development strategy has been laying the ground for a social protection system through the national expansion of the *Programme National Solidarite Familiale* (PNSF) and the establishment of a national social registry for targeting and referral to a number of social services. In this paper, we present new Proxy Means Test (PMT) models for targeting based on the 2017 household survey data (EDAM4). The paper finds that the developed PMT models, with separate targeting formulas for rural and urban areas, appear to perform well vis-a-vis inclusion and exclusion errors observed in similar country contexts. Ex-ante simulations also show that the planned expansion of targeted social assistance program, PNSF, using the proposed targeting approaches will result in nearly 0.7 percentage point reduction in poverty nationally and 3.4- 4.1 percentage reductions in the regions. These results reinforce the effectiveness of PMT targeting approach for social assistance programs in Djibouti when carried out in combination with geographic targeting in high-poverty districts. The results also show the relevance and effectiveness of PMT as a national targeting approach in urban regions and for an expanded national social assistance program.

JEL Codes: H55, H53, I38

Keywords: Poverty, Social Protection, Poverty Targeting, Proxy Means Test, Government expenditure and welfare programs, Social Registry, Social Protection Systems

¹Corresponding authors: Vibhuti Mendiratta (vmendiratta@worldbank.org) and Amr Moubarak (amoubarak@worldbank.org)

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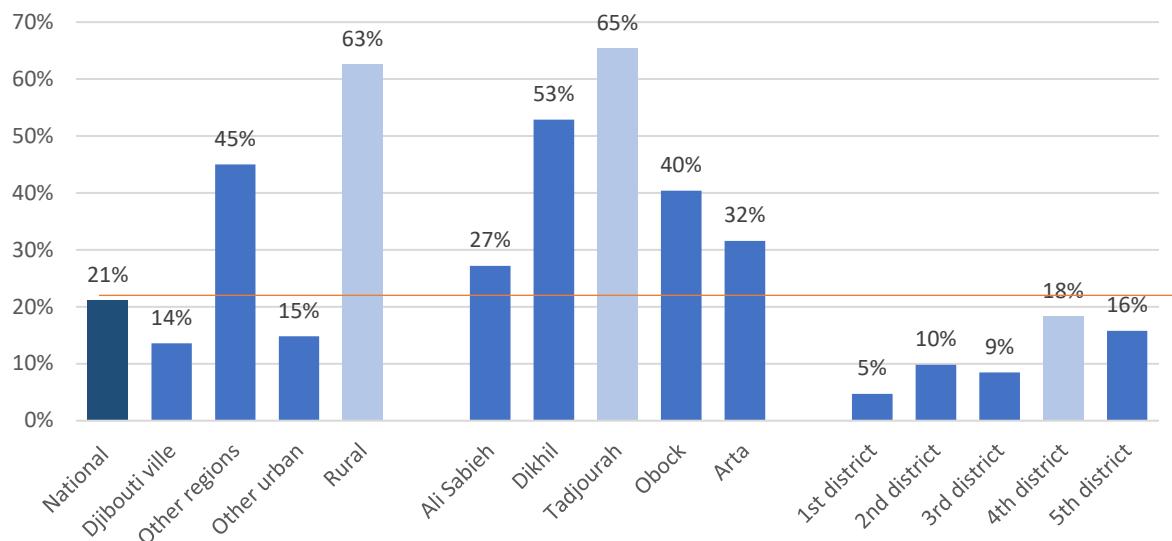
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Introduction and Background

Djibouti, a small lower-middle income country with a strategic geopolitical and maritime trade position, faces continued challenges in reducing extreme poverty and improving human capital outcomes. The small state faces chronic early childhood health and nutrition challenges that are compounded by high levels of poverty and growing inequality especially in rural areas. Limited arable land and rainfall have had adverse effects on livelihoods and contributed to continued volatility in the prices of basic food staples. These factors contribute to persistently high level of food insecurity and erosion of livelihood assets due to negative coping mechanisms. As of 2017, inequality is considered high with a Gini index of 0.42 – one of the highest in East Africa region (DISED, 2018). Figure 1 shows that an estimated 21.1 percent of the Djiboutian population lived in extreme poverty in 2017, spending less than DJF 117,783 per adult equivalent per year (equivalent to US\$2.17 per person per day in 2011 PPP). Rural areas which represent 15 percent of the country's population showed significantly higher rates with extreme poverty close to 62.6 percent. Finally, about 13.3 percent of the population was estimated to be living below the poverty line in Djibouti city. Among the five districts of the city of Djibouti, the fourth and fifth districts (together known as Balbala) have the lowest levels of consumption in Djibouti and the region.

Figure 1. Extreme poverty rates, by EDAM4 representative domains



Source: Authors' Calculations - EDAM4-IS

Note: Line across graph denotes the national extreme poverty rate

Djibouti's arid climate, basic food price volatility, and the increasingly frequent droughts have affected households' abilities to smooth consumption, invest in productive assets, and early childhood development. During drought spells, households' resort to negative coping mechanisms such as selling their livestock. The lack of local level demand for goods and services and limited livelihood opportunities, coupled with Djibouti's vulnerability to international prices of basic commodities exposes poorer households and urban dwellers across income categories to food insecurity. Among households who reported economic shocks, 83 percent of the poorest

households and 65 percent of the richest household's report experiencing food insecurity (DISED, 2014).

As for investments in human capital, Djibouti ranks 172 out of 188 in the Human Development Index (HDI).² Notable challenges include some of the highest rates of stunting and wasting for children under five.³ Famine and prolonged food and nutrition deprivation negatively affect cognitive development of children, especially during the women's prenatal and postnatal period (Agbor and Price, 2014; Almond et al., 2010). Djibouti's education sector is also characterized by low enrolment, inequitable outcomes, and relatively poor quality. More than half of students fail to complete primary school, and overall 30% of the school-age population remains out of school.

Social Safety Nets in Djibouti

Djibouti's approach to expanding social safety nets (SSN) has been increasingly aligned to poverty reduction and building of human capital challenges faced over the past few decades. However, safety nets coverage and generosity often face challenges to respond to drought spells and continued volatility in the costs of fuel and food since the early 2000s. A key pillar of Djibouti's poverty and human development strategy has been laying the ground for a social protection system through the national expansion of the *Programme National Solidarite Familiale* (PNSF) and the establishment of a national social registry for targeting and referral to a number of social services.

Progress in addressing these challenges has been through a reduction in poverty rate (headcount poverty) and reduction of the poverty gap – as well as through developing and reinforcing systems. Public financing has also been a second priority with the aim of reducing poverty in a sustainable way through expansion and financing and social safety nets and investments that improve livelihoods of the population in Djibouti-ville and the peripheries. The *Programme National Solidarite Familiale* (PNSF) has been especially focused on addressing issues related to poor health and educational outcomes especially for mothers and young children. Since the inception of the program as a shock-responsive anti-famine rural safety nets program, the program has been accompanied by community-level behavior change sessions aimed at promoting pre-natal and post-natal care, diversified diet, cognitive stimulation during the first 1,000 days among other awareness sessions that constitute the conditionality for the conditional cash transfers.

The inception of PNSF and associated social safety nets and in-kind support programs offered by the civil society in Djibouti is in contrast to the urban and price-subsidy schemes seen in most other social protection sectors in the Middle East and North Africa (MENA) region where the focus has been on rebalancing generalized subsidies on commodities (mainly energy products) with more targeted transfers to households while consolidating generous social assistance programs in the form of food rations and social pension schemes.⁴ Djibouti's response to severe

² At the time of this writing, data is not available to produce a ranking for Djibouti in the new Human Capital Index.

³ 28.9% of children under 5 years are underweight. There is stunting rate of 32.6% with 19.7% rate of severe stunting according to UNICEF.

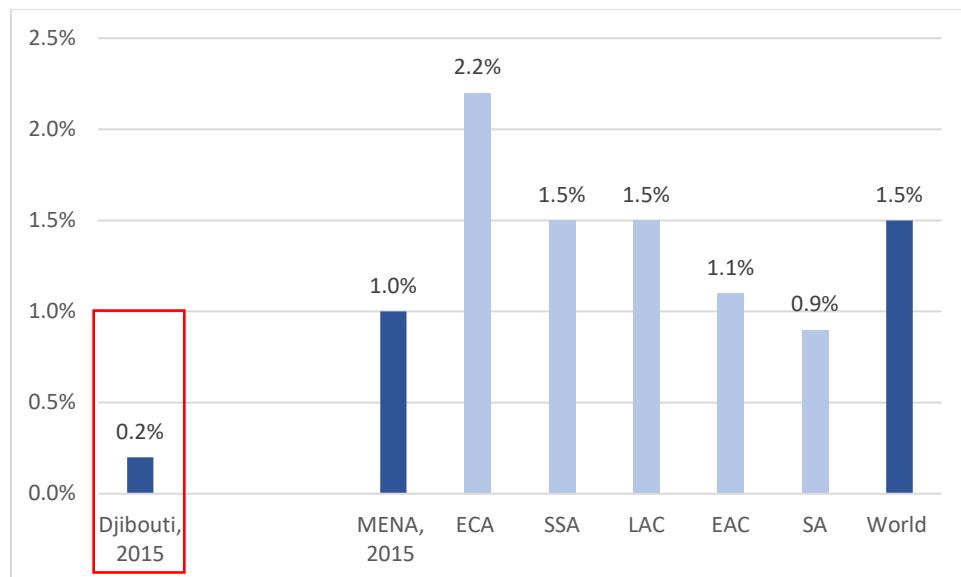
⁴ In the Middle East and North Africa, generalized price subsidies have been a major part of the "social contract" between governments and the people. Large scale subsidies are still pervasive, including in foods and fuels. Yet generalized subsidies are both costly and usually badly targeted. This is especially the case with energy products. Only 7 percent of fuel subsidy spending in poor countries benefits the poorest quintile of households, while 43 percent benefit the richest quintile. For example, in 2008, the poorest 40 percent of the population in Egypt received only 3 percent of gasoline subsidies (Sdralevich et al, 2014). Globally, the IEA estimates that only 8% of subsidies accrue to the poorest fifth of the population (IEA, 2012).

poverty, malnutrition, and poor health and child development outcomes drove its social protection strategy.

However, Djibouti's experience with introduction of a national poverty-targeted social safety nets programs remains quite nascent. Until the creation of PNSF in 2016, most social safety net programs had been established at the wake of drought shocks and were largely donor-driven initiatives (such as WFP, UNICEF, FAO, Islamic Development Bank, USAID, Norwegian Refugee Council) which were mainly focused on providing food to vulnerable populations outside of government systems and were not fully based on national poverty level and targeting approach. These programs were run through parallel systems leveraging humanitarian agencies presence, capacity, and technology solutions.

While Djibouti has moved in the right direction in design and implementation of social safety nets programs to address the most acute challenges facing the poor and vulnerable population, the scale and funding of an integrated SSN program remains inadequate to protect most poor and vulnerable groups. Expenditure on social safety nets in Djibouti remains low compared to regional and global spending as part of fiscal spending. While the Middle East and North Africa spends on average 1% of GDP on SSN, and sub-Saharan Africa spends 1.5%, Djibouti only spent 0.2% of GDP in 2015.

Figure 2: Social Assistance Expenditure as a Percentage of GDP (2015)



Source: Authors' calculations and ASPIRE database.

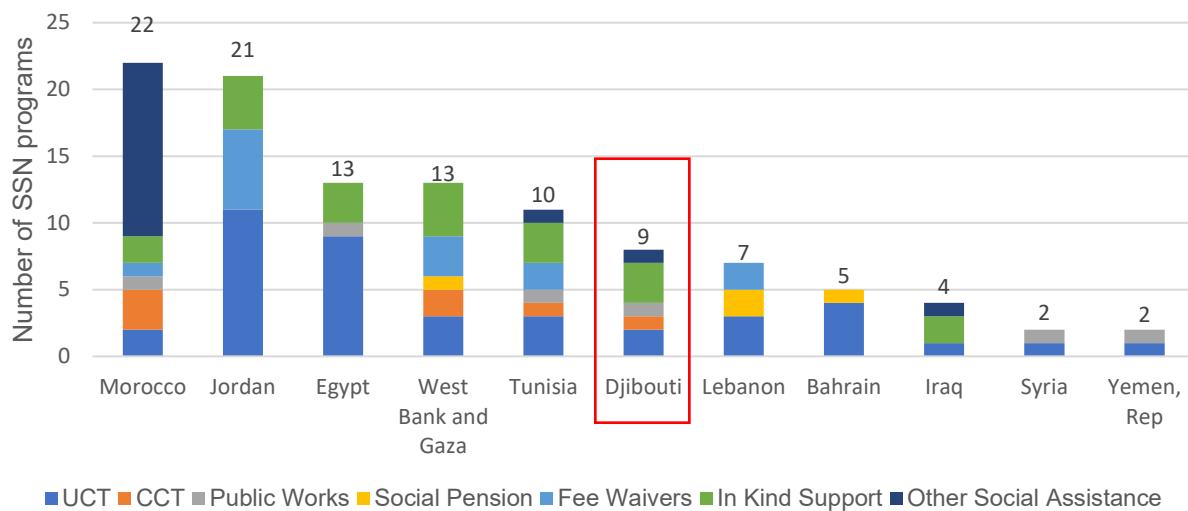
Note: Calculated individual programs expenditure as a percentage of that year's GDP (real GPD) and aggregated all programs by country. Data is administrative spending data.

It should be noted that the above graph does not include spending on fuel or food subsidies. Although generalized subsidies are generally seen as forms of social protection (especially for more progressive targeted commodities such as rice, flour and food stuffs), Djibouti spends little on generalized subsidies. This creates very little fiscal space for rebalancing spending from these

types of programs (which are generally pervasive in MENA, as well as horn of Africa countries including Ethiopia and Eritrea).

Accompanying this relatively low spending on social safety nets, Djibouti has 9 different safety net programs (Figure 3). Although in the case of Djibouti, the two largest programs, PASS and PNSF, both use the social registry to ensure efficiency and reduction of duplications in benefit delivery.⁵ When compared regionally, Djibouti has a lower total number of programs and relies heavily on the two programs to deliver benefits. In comparison, in Morocco, most programs are classified as “other social programs” and include variety of overlapping safety nets programs that aim to support the poor in providing education to children. In Jordan, Egypt, Lebanon and Bahrain most programs are unconditional cash transfers. In-kind and near-cash support is the second most prevalent form of SSN in the region. The high fragmentation of these programs leaves significant scope for improvement through consolidation and better use of the resources throughout the region.

Figure 3: Social Safety Net Programs by Program Type



Source: Author calculations and ASPIRE database.

Notes: UCT: Unconditional cash transfer. CCT: Conditional cash transfer

Djibouti's *Programme National Solidarité Familiale* (PNSF) is a conditional cash transfer program which makes up a large portion of the available SSN budget (Table 1). Besides regular

⁵ Administrative data collection generally utilizes available expenditure and program information provided by participating countries. In the case of Djibouti, a social protection review was conducted in 2015 – 2016 which identified relevant program. Although all efforts were made, not all programs that fit the definitions of social safety nets schemes were reported were reported in participating countries.

cash assistance, beneficiaries of the PNSF are also eligible for a subsidized medical insurance (under the *Programme d'Assistance Sociale de Santé* program, or PASS).

Table 1: Social Safety Net Programs in Djibouti⁶

Program Name	Program Type	Expenditure (USD) 2019
Zakat	UCT	..
Food distribution Program	Food, in-kind and near-cash transfers	..
Scholarships for Education	Other Social Assistance Programs	..
School Feeding Program	Food, in-kind and near-cash transfers	..
Food voucher (July-September)	UCT	500,000
University students (cantine and transport subsidy)	CCT	929,600
Social Assistance Pilot Program on Labor and Human Capital	Public Works	1,381,623
Peri-urban Voucher Program	Food, in-kind and near-cash transfers	..
PNSF	Rural and Urban Cash Transfer Program	1,521,000
IDA credit in support of PNSF (2020) ⁷		3,360,000

Source: Bank staff calculation, 2013-2019

Notes: UCT: Unconditional cash transfer. CCT: Conditional cash transfer

Djibouti's largest national program, PNSF, currently serves approximately 12,362 households, covering approximately 8.2 percent of the country's population.⁸ Financing is shared by the Government, World Bank, and European Union. The program is well on the way to becoming the cornerstone of a country-owned and adaptive Social Protection system. To that end, creating the fiscal space and investing in the institutional and capacity building to consolidate the PNSF as a flagship country-owned SSN system covering the needs of a broad section of the extreme poor is a key priority for GoD.

To support this effort, the World Bank is supporting the GoD in the expansion and system building elements of Djibouti's social protection system. The Integrated Cash Transfer and Human Capital Project (PITCH) is financing conditional cash transfers to 5,000 households outside the capital and in rural sub-prefectures with high poverty rates. Furthermore, PITCH is supporting the PNSF to develop accompanying measures related to participation in community-level behavioral change

⁶ As social insurance, the PASS subsidized health insurance program is not included here but nevertheless constitutes an important Government social program.

⁷ Integrated Cash Transfer and Human Capital Project (PITCH)

⁸ The average household size in the country is 6.4, according to EDAM4-IS. The National Institute of Statistics of Djibouti estimates the population at 962,451 at the time of writing. Therefore, it is estimated that currently the program covers 79,117 individuals which represents about 8.2 percent of the population.

communication sessions to nudge beneficiaries towards building their human capital. The National Social Protection Strategy (2018-2022) envisages eventually covering approximately 20,000 extreme poor households in Djibouti under PNSF, thus leading to an increase in coverage of the PNSF program to around 13.3 percent of the population. The expansion of PNSF will represent close to an increase of 0.8 percentage points in GDP spending on social safety nets (close to 1% of GDP) assuming sustained Government financing to cover 15 percent of the population. This increase would therefore bring Djibouti closer to the MENA average in terms of spending on social safety nets.

Based on the distribution of the population from EDAM4, the rural population represents 15 percent of the total population, but it hosts about 45 percent of the population considered as extreme poor and 62 percent of all (expected) PNSF beneficiary households (Table 2). On the other hand, 76 percent of the total population lives in Djibouti city while 49 percent of the poor population as well as only 32 percent of PNSF beneficiary households live in Djibouti city. Finally, in terms of magnitude, the fourth and fifth districts—belonging to the community of Balbala—are the residence of nearly 37 percent of the poor population and 22 percent of PNSF beneficiary households in the country.

Table 2: Distribution of Extreme Poor, Overall Population as well as PNSF beneficiaries across Locations

	Extreme poor (%)	Overall population (%)	PNSF beneficiaries (number of households)	PNSF beneficiary households (%)
<i>by regions</i>				
Djibouti city	49	76	4,000	32
Ali Sabieh	7	5	1,423	12
Dikhil	16	7	2,259	18
Tadjourah	17	5	2,670	22
Obock	5	2	1,272	10
Arta	6	4	738	6
National	100	100	12,362	100
<i>by location</i>				
Urban	55	85	4,674	38
Rural	45	15	7,688	62
National	100	100	12,362	100
<i>within Djibouti-ville</i>				
1st district	2	8	254	2
2nd district	8	17	744	6
3rd district	2	5	295	2
4th district	20	24	1,598	13
5th district	17	22	1,109	9

Source: Authors' Calculations - EDAM4-IS. Information on PNSF beneficiaries is from Ministry of Social Affairs and Solidarity of Djibouti.

Targeting Performance of the Updated Proxy Means Test Formula

The expansion of PNSF relies on a strengthened and updated targeting mechanism based on *proxy means testing* (PMT) using the latest household survey of 2017. Here, we present the results of an analytical exercise using the EDAM 2017 data to build a prediction model that can be used to: (i) estimate the consumption level of a households based on observable characteristics, and (ii) support the ministry in eligibility determination of PNSF and other social programs using a set of eligibility criteria including PMT. The following sections discuss the findings of this exercise.

A Proxy Means Test (PMT) application using EDAM 2017

In 2013, the first PMT formula was developed for Djibouti utilizing EDAM data. This was used by the *Secreatariat d'Etat des Affaires Sociales* (SEAS) to target the most vulnerable households in Djibouti. The PMT measure was used in geographic regions targeted by the GoD where SEAS was operational. Given the strong economic growth observed in the country in preceding years and the expected expansion of the national social assistance program, PNSF, the Government requested the support of the World Bank to explore whether the introduction of an updated PMT formula is required to better reflect the current conditions of poor households in Djibouti. The proposed expansion and increased financing came immediately following the completion of the EDAM4 in 2017 which presented an opportunity to utilize the findings of EDAM 2017 for 2019 recertification. This allowed for an update of the poverty profile, welfare, patterns of consumption and shocks affecting households. These, in turn, informed the utilization of newly available data to reconstruct the 2013 PMT formula.

As is the case in most countries, anti-poverty social programs often rely on proxies of households' observable characteristics in combination with geographic, categorical, and some asset filters. In countries where administrative data are not accessible for means-verified targeting, households' reported information is used for eligibility determination. This reported information is assigned a weight based on the developed prediction model. PMT models are advanced regression-based statistical approaches to determine the relationship between households' indicators and consumption/ income. Often times, these weights are seldom updated as they rely on the infrequent and national household surveys to produce new proxies of assets and demographics.

There are challenges associated with all targeting approaches including PMT. PMT models are known to have certain limitations that can be both methodological and operational in nature.⁹ Methodologically, this can include errors of inclusion or errors of exclusion. At times, these measures are systematic – e.g., assigning a significantly higher score for large households or households with a large number of children which may systematically exclude equally smaller, but equally desolate households. To resolve this, the section below discusses potential errors of inclusion and exclusion and performs a tabulation of key observable characteristics.

A widely cited limitation relates to success of PMT approach in responding to shocks or uninsured risks. PMT uses information on the ownership of long-term assets to predict welfare and as such can be useful in identifying the chronic poor and determining eligibility for programs that provide long-term support (Del Ninno and Mills, 2005). Nevertheless, it does not protect the poor from

⁹ See the discussion in Brown et al. (2018) on PMT for nine African countries.

uninsured risks and as such applying PMT model to short-term targeting generates errors. In other words, when testing the performance of a social program using a PMT model based on cross-sectional data, there is a limitation that the PMT model is not able to distinguish between the program's ability to protect the poor against shocks versus promote long-term poor. Having access to panel data can resolve this to some extent, as shown by Ravallion et al. (1995). Other approaches recommended by Leite (2016) include PMTplus method that allows small shock-related adjustments to the PMT to reduce inclusion errors in times of drought and price shocks as well as to examine the most up-to-date geographic data to identify the shock-affected areas (geographic targeting) and then carry out a quick data collection exercise to gather food-insecurity indicators to improve the precision of the model. Other type of social programs such as guaranteed welfare schemes that offer people the right to work under certain conditions and circumstances also do better in terms of protecting the poor against shocks.

In addition to these methodological challenges which can be, in part, resolved through robustness checks discussed in the forthcoming sections, PMT may face operationalization challenges for effective targeting. These include programming errors in assigning weights or lack of clarity of social workers in posing questions and inputting data. Additional challenges may include fraud and misreporting information. These operational challenges are often addressed through hands-on technical assistance in PMT programming, training and on-site support to social workers in the executing agency as well as communication campaigns to potential beneficiaries.

Nevertheless, there are contexts in which the application of this approach is warranted and helps build a path for a strong SSN. By planting the idea of targeting based on analytics coupled with support to the local capacity, the implementation of the PMT now can set the stage for the establishment of more efficient programs in the future. Del Ninno and Mills (2015) argue that the use of PMT models useful when informal economic activities or own production represent large shares of total household income. Given Djibouti's high level of informality and weakly integrated information systems, a PMT model thus can be an informative tool to help achieve the objective of ranking and finding the most vulnerable population. At the same time, PMT models have been shown to provide fairly strong targeting results for the chronic poor.

In this section, we describe the estimation of a predictive PMT model that can help identify vulnerable households by collecting data on a short list of observable characteristics (proxies). To develop the PMT model and choose observable characteristics, we rely on PMT models developed in other countries, local Djiboutian context as well as verifiability of characteristics (proxies) by social workers. We first describe the methodology of the PMT, followed by the estimated model. We conclude by describing the performance of the model.

Methodology

Consumption per capita is the welfare aggregate used to measure and predict poverty. An ordinary least squares (OLS) estimator is used to predict the natural logarithm of consumption per capita on the set of explanatory variables. Formally, the model is specified as:

$$\ln W_i = \alpha + X_{ij}\beta_j + \varepsilon_i \quad (1)$$

where W_i is the log of consumption per capita¹⁰ per household (welfare aggregate), X_{ij} is a vector of characteristics of j variables (poverty predictors) for i households, β_j are the coefficients (weights) of the poverty proxies, α is the constant and ε_i the error term.

The goal of the exercise is to maximize the R-squared – the explanatory power of the model – and to minimize the inclusion (leakage) and exclusion (undercoverage) errors. Table 3 presents the different possible performance scenarios. Households will be successfully targeted (S1 and S2) when poor and non-poor households are beneficiaries and non-beneficiaries, respectively. On the other hand, when poor households are non-beneficiaries because predicted as non-poor and conversely, non-poor household beneficiaries, these will incur exclusion (E1) and inclusion (E2) errors, respectively. From this set of possibilities, the following concepts will be evaluated for targeting efficacy of the proposed updated formula:

- (i) *Coverage rate*, as the ratio of beneficiaries to total population ($M_1/N * 100$).
- (ii) *Leakage rate*, as the ratio of inclusion error to total beneficiaries ($E_2/M_1 * 100$).
- (iii) *Undercoverage rate*, referring to the ratio of exclusion error to total poor ($E_1/N_1 * 100$).

Performance of the models is tested by comparing undercoverage and leakage rates between PMT.

Table 3: Inclusion and Exclusion Errors

	Poor	Non-Poor	Total
Beneficiary	Successful Targeting (S ₁)	Inclusion Error (E ₂)	M ₁
Non-Beneficiary	Exclusion Error (E ₁)	Successful Targeting (S ₂)	M ₂
Total	N ₁	N ₂	N

Other Key Considerations

In practice, other considerations need to be taken into account in choosing a particular PMT model. One objective, for instance, could be to raise the welfare of the poor, in which case minimizing the exclusion error can be seen as a priority for program administrators. On the other hand, officials may be interested in keeping costs of the program contained and may therefore choose to minimize the errors of inclusion at the expense of increasing exclusion errors (E1). Finally, some administrators may find it difficult to verify regressors in the formula deemed to have a statistically significant which means that the revised models may have a lower explanatory power (for example, reduced adjusted R-squared). Finally, the administrative costs of implementing one (or many) PMT models in an effective way should also be taken into account.

The Model

As a first step, the team looked at reconstructing the PMT model developed in 2013 and applying it to the specification to the EDAM 2017 data. Simulation of the existing model showed higher undercoverage (exclusion error) and lower national coverage in 2017/2018 compared with 2013 (Table 4). The results are not surprising as elements of Djibouti's economic growth, poverty, and inequality challenges, as well as shock incidence has changed since EDAM3-IS, resulting in a

¹⁰ Using the logarithm of consumption per capita improves the fit of the model by transforming the distribution of consumption per capita to a more normally-shaped bell curve.

weaker performance of the 2013 PMT. A revision of the model, which was previously robust in identifying poor households, is necessary to account for the progress and change Djibouti has experienced since 2013.

The re-estimation of the 2017 PMT tested the old covariates, as well as new correlates (that aid as *proxies*) of consumption (and in turn of poverty). The simplest approach to the re-estimation would be to repopulate the 2013 PMT with new data in order to update the beta coefficients. However, this would limit the potential of the probability model to accurately predict current levels of welfare. Therefore, a new model is estimated with EDAM 2017 data.

Table 4: Performance of PMT 2013 using EDAM 2013 and EDAM 2017

EDAM 2013				EDAM 2017		
Decile	Coverage	Under-coverage	Leakage	Coverage	Under-coverage	Leakage
1	8.3%	44.3%	32.7%	4.1%	69.6%	25.4%
2	20.4%	32%	33.1%	11.7%	56.5%	25.5%
3	32.4%	24.7%	30.2%	18.4%	51.0%	20.0%
4	42.5%	19.7%	24.3%	24.5%	48.8%	16.5%
5	52.1%	16.4%	19.9%	31.3%	47.3%	15.7%
6	62.3%	13.4%	16.6%	39.1%	42.1%	11.1%
7	71.8%	10.1%	12.4%	48.5%	37.1%	9.1%
8	82.7%	5.4%	8.5%	57.9%	31.5%	5.2%
9	91.7%	3%	4.8%	74.8%	19.1%	2.7%

Source: Authors' calculations using EDAM3 and EDAM4-IS

The revised 2017 PMT models include a range of poverty predictors from 5 categories of household-level indicators. The choice of predictors is determined by two factors: (i) the correlation with consumption per capita, which is important for accurate predictions, and (ii) the verifiability of the predictor by social workers who conduct home visits, which is important to determine the accuracy of the information imputed in the PMT formula. Proxies were selected using stepwise estimation with a 10% significance level for removal from the model. Therefore, the final model selection¹¹ was informed by backward-selection estimation and applying analytical population weights. The different categories of predictors assessed to determine probability of being in poverty ranged from 54 variables in the national model to 78 variables in the urban model and are the following. *Household characteristics*, such as household size and dependency ratio. *Dwelling characteristics*, such as materials used to construct walls and roofs, as well as access to basic services like electricity, improved sanitation and water. *Characteristics of the head of household*, such as education level and employment status. *Location*, such as region of residence. *Ownership of durable goods*, such as televisions, refrigerators, radios, etc. Most of these indicators are difficult to falsify or unlikely to be falsified. Unannounced household visits by social workers also limit the ability to falsify information.

¹¹ This is an active program that has recertified beneficiaries and thus the team has decided not to disclose the model and the associated estimates.

The R-squared for the national, urban and rural model are 0.74, 0.70 and 0.52 respectively. We find that ownership of durable goods, such as cellphones, televisions, refrigerators, bicycles, mattresses, and radios, is associated with higher predicted welfare. Household demographic indicators such as size and dependency ratio – the ratio of children and elders to adults – are negatively correlated with welfare. Large households with a high prevalence of financially dependent children and elders are not surprisingly predicted poorer. The poorer regions of Dikhil and Tadjourah are associated with higher poverty likelihood. Educated heads of household and those working in the public sector are less likely of being poor. Households living in villas or apartment buildings are less likely of being poor compared to those living in tents, makeshift accommodation, ordinary housing, or collective housing.

Performance

A common default is to estimate a national PMT model using a nationally representative household survey instead of evaluating combination of explanatory models based on the latest available poverty profiles. To that end, the heterogeneity between urban and rural communities called for estimating two distinct models for each environment. PMT predictors, such as dwelling characteristics (e.g.: materials used to build roof, walls, and floors), are not easily comparable across regions. Thus, following consultations with partners and government representatives, we present here the results from a single national model, and a regional model that combines two separate PMT formulae for rural and urban households.¹²

Conventionally, the performance of a PMT model can be evaluated by measuring predictions errors.¹³ Two indicators are of key interest. First, the exclusion error or under-coverage occurs when households are flagged as non-beneficiaries by the PMT formula, but in reality, a more detailed observation of their consumption level would have put them below the eligibility threshold (which many times implies that they are poor). Second, the inclusion error, or leakage rate refer to the households that are classified as beneficiaries to the program due to a low PMT score, when in fact they may not be poor or their real consumption levels are above what a given program considers to be the eligibility threshold. These rates were simulated at different levels of the consumption per capita distribution (i.e. deciles), as well as the 25th and 35th percentile as these are close to the national extreme and global poverty rates estimated by DISED¹⁴ (21 percent and 36 percent, respectively).

Table 5 compares the performance indicators of two models. One is a national model that applies one formula to the entire country. The second model allows the formula to vary between urban and rural areas and is labeled “Flexible”. The results on performance indicators are presented at the aggregate (national) level for ease of comparison. There are no significant differences between the exclusion and inclusion errors of the two models, nor one appears to be clearly preferable to

¹² A third model for 3 distinct regions was also estimated: City of Djibouti PMT, Other Urban Areas PMT (including only *chef lieux*), and a Rural PMT. However, for logistical reasons, such an approach was not favored.

¹³ Each specification was obtained using stepwise regression in STATA. Multicollinearity among regressors on the final specifications was formally tested using the Variance Inflation Factor (VIF) ratio. No multicollinearity was detected given that all indicators had a ratio below 5. Mean VIF for the three models (national, urban, and rural, respectively) stood at 1.75, 1.35, and 1.64."

¹⁴ Poverty rates from DISED are based on an adult equivalent scale. In results not shown, comparable models have been produced to estimate performance based on an adult equivalent scale. The GoD will have to take into consideration potential differences of these models in defining the targeting criteria of programs that will use the PMT.

the other. As a rule of thumb, the PMT models are assessed based on their performance at the 30th percentile. It is, however, also interesting to use the 35th percentile as guidance of performance. The reason is that, in the case of Djibouti this level is qualitatively similar to poverty in per capita terms, the upper official poverty rate, and provides relatively more desirable levels for the performance indicators. This model assumes that the population of interest is concentrated in the bottom 30 or 35 percent of the distribution. The national model appears to be slightly better in terms of exclusion, while the flexible model performs better in terms of inclusion. A targeting at the 35th percentile would lead in the national (flexible) model to an undercoverage rate of 24.8 percent (25.1 percent) and a leakage of 20.6 percent (19.6 percent). These as well as those at the rates for the 30th percentile are empirically low rates of error when compared to other settings (Figure 4). Finally, Figure 5 shows overlapping cumulative density functions of log expenditures per capita for the data collected in EDAM 2017, the national model and the flexible model. The vertical red line is at the 30th percentile of the distribution. This figure shows that the flexible model performs slightly better at mirroring the actual distribution of consumption expenditure for the poor population.

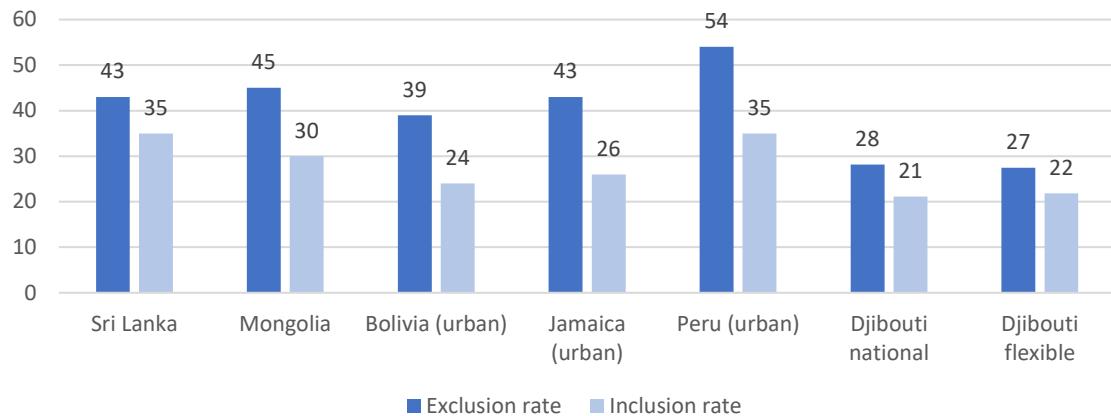
Table 5: Performance National and Flexible PMT Models

Percentile	National			Flexible		
	Coverage	Exclusion	Inclusion	Coverage	Exclusion	Inclusion
10	8.5%	41.7%	31.5%	8.4%	42.3%	31.1%
20	17.1%	35.0%	23.9%	16.6%	35.5%	22.2%
25	23.8%	29.1%	25.4%	22.9%	30.9%	24.5%
30	27.3%	28.1%	21.1%	27.8%	27.5%	21.8%
35	33.3%	24.8%	20.6%	32.6%	25.1%	19.6%
40	39.3%	21.6%	20.1%	38.8%	21.6%	19.0%
50	50.4%	16.4%	17.0%	49.7%	17.1%	16.4%
60	61.4%	12.4%	14.4%	61.7%	12.4%	14.8%
70	72.4%	9.0%	12.1%	72.6%	8.8%	12.0%
80	83.3%	4.4%	8.2%	82.7%	4.7%	7.8%
90	93.2%	1.3%	4.6%	93.1%	1.3%	4.6%

Source: Authors' calculations using EDAM4 data.

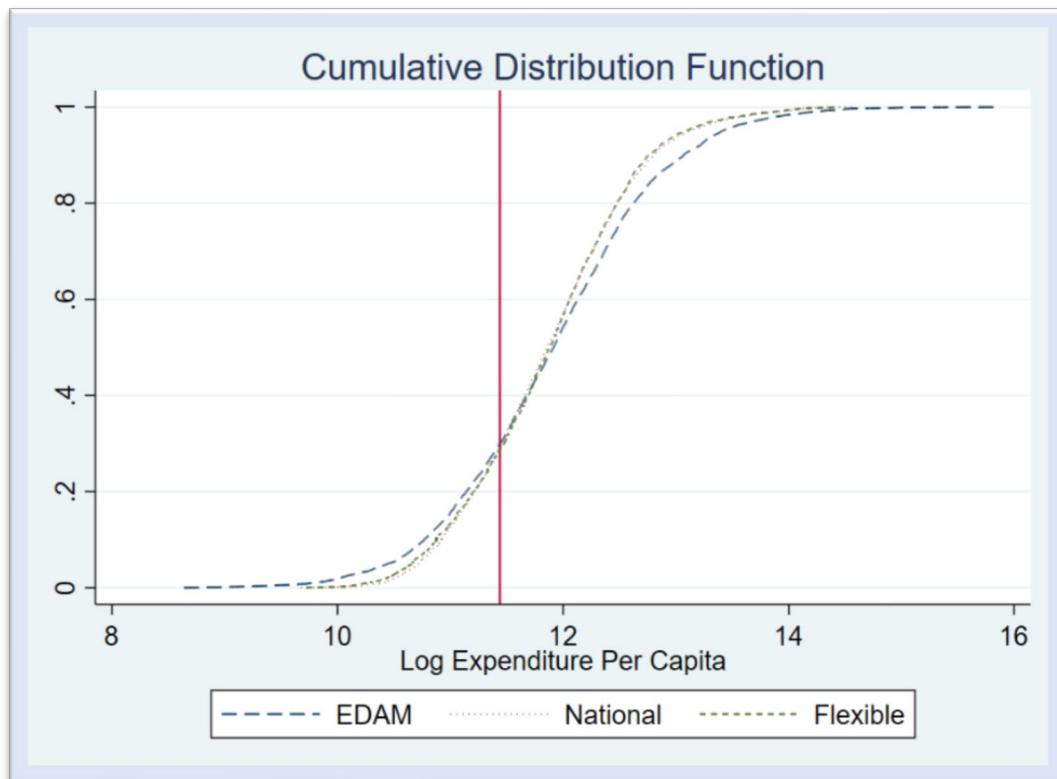
Notes: Coverage, exclusion and inclusion rates for the flexible model are obtained by putting together predictions of two separate models: an urban and a rural model.

Figure 4: Estimated Errors of Inclusion and Exclusion for PMT model in Djibouti (30th percentile) and International Comparators



Source: Authors' calculation using EDAM4-IS(Djibouti); and compilation in Atamanov *et al.* (2015) from Grosh and Baker (1995), Narayan and Yoshida (2005) and Araujo and Cararro (na).

Figure 5: Cumulative distribution of log consumption expenditure per capita: data versus models



Source: Authors' calculations using EDAM4-IS data.

Additional performance indicators of the PMT model

Performance in population subgroups

Overall, homogeneity is greater among households in rural settings than households in urban regions - performance among rural communities is therefore expected to be more accurate than among urban families. A common concern by partners on the ground is the failure of PMT models to predict poverty accurately for small and large households (see discussion of household distribution below). This concern is tested by assessing the performance of the specifications described above¹⁵ for different subsets of the population. The focus is on three groups: small households defined as household sizes below or equal the 10th percentile (i.e. 3 members), large households as those above or equal to the 90th percentile (i.e. 10 members), and small and elderly households (defined as those with at least 1 elderly member -60 years old or above- in a two-person household at most). These households account for 13 percent, 13 percent and 1 percent of the population sample, respectively. Poverty incidence among these groups is, respectively, 16 percent, 29 percent, and 21 percent (national poverty rate being 21 percent).

As a sensitivity analysis, we present performance indicators of the flexible PMT specification for these three subgroups in Table 6.¹⁶ There is no clear evidence suggesting that the PMT would significantly underperform in these population subgroups. For instance, using the results from Table 5 above, we find that rates of exclusion are lower for all three populations of concern than among the overall population. At the 35th percentile undercoverage is 23.2 percent for small households, 15.1 percent in large households, and 16.5 percent in small-elderly households, whereas it is 25.1 percent at the population level. Notably, leakage rates are higher, especially in the case of large households (30.2 percent), compared to the national average of 19.6 percent.

Table 6: Performance of the Proposed Flexible PMT Model for Subsets of Population

Percentile	Small Households		Large Households		Small & Elderly Households	
	Undercoverage	Leakage	Undercoverage	Leakage	Undercoverage	Leakage
10	50.1%	39.1%	29.6%	43.6%	61.9%	58.6%
20	34.2%	33.1%	19.2%	26.0%	14.2%	36.1%
25	30.6%	28.5%	18.2%	35.1%	18.4%	29.9%
30	25.5%	25.1%	13.8%	32.4%	18.2%	23.0%
35	23.2%	23.0%	15.1%	30.2%	16.5%	25.4%
40	19.2%	21.1%	6.7%	25.0%	9.8%	24.4%

Source: Authors' calculations using EDAM4 data.

¹⁵ Additional estimations were done following the flexible model PMT where the household size was included as a series of *dummy* variables instead of using it in continuous form. The idea was to allow the prediction model to non-parametrically estimate differences in consumption across households of different sizes and that differences could vary between smaller and larger households. This econometric specification worsened exclusion and inclusion errors.

¹⁶ Results for the national model are qualitatively the same.

Performance in the bottom of the distribution

Following Grosh and Baker (1995), we further test the desirability of an alternative to reduce measured exclusion errors by using the poorer segment of population to run the predictive PMT model. The argument is that by focusing on the poorest half of the population as the basis for the formula (and assuming that richer individuals and households are unlikely to apply to a social program) the approach can lead to much lower exclusion errors. Certainly, the assumption that no one from above the program cutoff would apply for benefits will not apply cannot be guaranteed.

The national and flexible models were re-estimated by fitting only the bottom 55 percent of population (i.e. a truncated model). This specification included 35 variables (instead of the 50 plus of the previous models). Table 7 shows the results obtained from : i) the re-estimation of both national and flexible models to only the bottom of the population; ii) using the typical cutoff of 35th percentile; and iii) showing the results of whether the assumption on richer households being able to apply to (and be considered for receiving benefits of) a given social program using the PMT formula.¹⁷ Restricting the sample to the bottom 55 percent of the population and using the truncated model generates errors of exclusion of 11 percent regardless of our assumption on who is able to apply to the program. This implies that the program would miss about one actual poor person from ten. Errors of inclusion are between 23-34 percent.

Table 7: Estimates for Errors of exclusion and inclusion for a truncated PMT model assuming self-selection at program registration stage

	Anyone applies to the program		Only bottom 55% applies to the program	
	Exclusion	Inclusion	Exclusion	Inclusion
National model	11%	34%	11%	23%
Flexible model	11%	34%	11%	23%

Source: Authors' calculations using EDAM4.

If we need to compare between the models presented above and the truncated model, it is necessary to make sure we select a cut-off point producing approximately similar program's participation rates (and thus, the identical budget). Aiming for a total participation of 32 percent, the relevant cutoff for the national/flexible models is the 35th percentile, whereas for the truncated model it is 25th percentile. Thus, if we predict errors using these cut-offs, we find that exclusion (inclusion) rates under the national and flexible models are around 25 percent (20-21 percent). Meanwhile, the truncated model (and a cut-off of a 25th percentile) would lead to an exclusion rate of 16-18 percent and an inclusion rate of 33 percent. Therefore, the truncated model performs better in terms of targeting poor people but has higher leakage.

The performance indicators associated with the PMT models presented here indicate that there is no clear "winner" in terms of providing the least errors across all dimensions. It is therefore crucial for implementing agencies to incorporate additional considerations based on their mandate to

¹⁷ Tests using VIF ratio were also performed in each mode for multicollinearity. The ratios were 1.62, 1.27, and 1.53 for the national, urban and rural models, respectively.

further scrutinize the model on the ground in the context of Djibouti and to decide the approach to follow or whether additional filters are need as “inclusion criteria” or “categorical targeting” (e.g.: female-headed households, widowed-headed households, etc.).

Simulating an expansion of PNSF

Using information from the PMT models which allows a differentiation between the urban and rural setting (i.e. model 2 without truncation), we run the following hypothetical scenario of an expansion of the PNSF to illustrate the potential of the application of a PMT model during Government planned expansion of the program over the next few years. We assume that the full value of the transfer is added to total household expenditure and the we compare it to the poverty line. Specifically, we took two cases proposed by GoD:

- (i) the PNSF is expanded nationally; and,
- (ii) The PNSF is expanded to rural areas only.

For each of these cases, we make the following set of assumptions were adopted:

- a) The PNSF is rolled out using the PMT model proposed to identify and rank (based on households' needs) potential beneficiaries. The PNSF is assumed to expand to an additional 5,000 households or approximately 32,000 additional individuals. If the government sustains domestic financing for the program, this would mean only an additional 3.38% of the population is covered.
- b) We use the EDAM2017 data to obtain a PMT score for all households (i.e. assuming that all households apply to the PNSF program and get a score). Households with the most needs (i.e. the lowest scores) are then ranked higher than households with higher scores
- c) The benefit level for PNSF will be around 56 USD per household per month to the new identified beneficiaries.¹⁸
- d) There are no behavior responses (changes to the labor decisions or consumption patterns for instance) as a result of receiving the program that may impact overall level of welfare post-transfers

Under these assumptions, new beneficiaries find themselves with a higher level of consumption per adult when compared to a situation prior to program expansion. As is the case with most social assistance programs, increases in welfare will result in reduction of overall poverty gap and decrease in poverty headcount. Table 8 presents some of these key results.

When the program is expanded nationally, there is a 0.6 percentage points statistically significant decrease in poverty in the country as a whole, but with substantial variation across regions. In particular, poverty in Tadjourah decreases by 4.5 percentage points. Poverty in the capital city decreases only slightly. This result may directly follow from the fact that higher levels of deprivation are found in regions that are heavily rural and thus under the simulation get much higher priority under the new PNSF. The poverty gap declines from 7.1 to 6.5 nationally. When PNSF is expanded to rural areas only, we find even sharper decreases in poverty in all the regions.

¹⁸ There are few households in the EDAM4 that declare currently receiving PNSF benefits. We assume they keep their current benefits.

About 8 percent of the population in rural Tadjourah is lifted out of poverty. Overall, the decline in poverty rate is slightly higher when the program is targeted at rural households only.

Table 8: Simulated Poverty Rate Changes Following Expected PNSF Expansion

	Expanded nationally		Expanded to rural areas only	
	Ex-ante	After expansion	Ex-ante	After expansion
Djibouti city	13.6%	13.5%	13.6%	13.6%
Ali-Sabieh	27.2%	25.5%	27.2%	24.4%
Dikhil	52.9%	49.3%	52.9%	48.6%
Tadjourah	65.4%	60.9%	65.4%	60.2%
Obock	40.4%	39.9%	40.4%	39.9%
Arta	31.6%	31.1%	31.6%	31.0%
National	21.1%	20.5%	21.1%	20.4%
Gini coefficient	41.6	41.1	41.6	40.9

Source: authors' calculations using EDAM4.

We also simulate an alternative scenario assessing the impact of a hypothetical expansion of the PNSF under a mixed implementing strategy. In this second simulation, eligibility is based on using both the PMT and geographical targeting. We simulate this scenario as the logistics and administrative costs of running a PMT nationally may be too high. In light of pervasive poverty in rural areas, a randomly assigned assistance package in rural communities coupled with PMT-targeting in the capital city could potentially reduce costs. At the same time, applying a PMT targeting in a zone with high population density such as the capital, may be cost-effective.

Using the same PMT model (model 2 without truncation), we run the following hypothetical scenario:

- a) The PNSF is assumed to expand to an additional 5,000 households.
- b) The PNSF provides around 56 USD per household per month to the identified beneficiaries.
- c) We assume there are no behavior responses (changes to the labor decisions or consumption patterns for instance) as a result of receiving the program
- d) The PNSF is randomly assigned among rural households based on the percentage of poor population living in either rural areas or in the City of Djibouti. This implies for instance that if 20% of poor households live in Dikhil then 1,000 (20% of 5,000) households in Dikhil will randomly receive the PNSF expansion.
- e) PNSF expansion for the City of Djibouti will be based on the percentage of poor households living there but selected through the PMT scores generated by the model (and not random selection). In this case, the lowest PMT scores are ranked first and we assume that all households apply to the program.

Table 9 presents the results from the second simulation. Under the assumptions and conditions outlined above beneficiaries of the PNSF expansion have a higher level of consumption per adult equivalent than before the expansion. This leads to an overall decrease in poverty nationally and regionally. Overall, there is a 0.6 percentage points statistically significant decrease in poverty in

the country as a whole. Similar to the first simulation there are substantial differences across regions. Tadjourah experiences the largest percentage point decrease in poverty (4.1 p.p.) and Obock the highest percentage decrease (9% as the result of a 3.6 percentage point drop in poverty). There is also an observed decline in inequality in the country.

Compared to the results from a PMT-exclusive targeting, the national poverty rate is reduced slightly more under this strategy, but this difference is not statistically significant (0.6 percentage points versus 0.7 percentage points). From a regional perspective, poverty in Djibouti Ville, Ali-Sabieh, Dikhil, and Tadjourah is not reduced as much under the second simulation. In light of these findings, and with consideration to costs, we observe that a mix of PMT and geographical targeting shows promising results. However, it is up to government authorities to evaluate the most efficient approach to distribute benefits in rural areas given the known high levels of poverty.

Table 9: Simulation of the Impact of the Alternative Targeting Model on the Poverty Rate following PNSF Expansion

	Ex-ante	After expansion
Djibouti ville	13.6%	13.4%
Ali-Sabieh	27.2%	26.1%
Dikhil	52.9%	50.5%
Tadjourah	65.4%	61.3%
Obock	40.4%	36.8%
Arta	31.6%	29.1%
National	21.1%	20.4%
Gini coefficient	41.6	41.1

Source: Authors' calculations using EDAM4.

Conclusion

This paper shows the need for and the role social safety nets is expected to play in consumption smoothing for poor and vulnerable households in Djibouti, specifically in terms of poverty reduction and reduction of inequality. Expansion of nationally financed and sustainable conditional cash transfer programs is especially important given the frequency of economic shocks affecting households, observed negative coping strategies of households (most pervasively in rural regions) and lack of investment in early childhood development practices. This is reaffirmed based on the EDAM4 poverty profile using 2017 data.

The paper also highlights that the introduction of a PMT to the eligibility determination stage of the national social assistance program, PNSF, plays an important role in providing a ‘layer’ for the identification of cash transfer beneficiaries nationally and at the regional level. As analysis shows, the application of PMT models using recent data collected in 2017 from the EDAM4 help to capture the livelihoods of Djiboutians as accurately as possible.

Overall, simulation of the existing model showed higher undercoverage (exclusion error) and lower national coverage in 2017/2018 compared with 2013. The results are not surprising as elements of Djibouti’s economic growth, poverty, and inequality challenges, as well as shock

incidence. The newly proposed PMT models appear to perform well vis-a-vis inclusion and exclusion errors observed in similar country contexts.

The potential of the PMT models and the results presented here to inform the design of policies is still high. Simulating the expansion of the program nationally, there is a 0.6 percentage points decrease in poverty in the country as a whole. When PNSF is expanded to rural areas only, we find even sharper decreases in poverty in all the regions. About 8 percent of the population in Tadjourah, for example, are lifted out of poverty. Overall, the decline in poverty rate is slightly higher when the program is targeted at rural households only. When simulating an alternative targeting model, poverty in Djibouti-ville, Ali-Sabieh, Dikhil, and Tadjourah is not reduced as much under previous simulations. In light of these findings, and with consideration to costs, we observe that a mix of PMT and geographical targeting shows promising results.

Looking ahead, the PMT models offer a great potential to improve targeting and eligibility determination for new beneficiaries in Djibouti, especially as the GoD increases its national financing of SSN programs. Currently, SSN spending remains quite limited in Djibouti. The challenge is compounded by the fragmentation of SSN programs as there are 9 different safety net programs for a population of 962,451 individuals. Operationalization of the PMT programs remains critical, not only for the expansion of the PNSF but also for the other programs which currently follow different approaches to targeting. But the road ahead will continue to be challenging for Djibouti to secure the financing and to reinforce cost-effective targeting and program delivery mechanism given the restricted budget.

As the program expands and number of beneficiaries increase in Djibouti, additional analyses could help complement the results presented here. In particular, the next analytical steps could be expanded in at least two ways. First, by conducting a comparison between the population of current beneficiaries of PNSF and the population that was used in estimating the PMT models. Should the demographic and economic characteristics be significantly different between the survey population and, say, the pool of households that will be re-certified to a program, caution should be used in the application of a new PMT model to “out-of-sample” populations. Second, more analysis should be done to explore the implications of official poverty rates being expressed in adult equivalent terms and PMT models in per capita terms. The eligibility definition and criteria should follow the most informative strategy for the government and should be taken into account for the classifications of vulnerability shown in in this analytical exercise.

References

- Araujo, C. and Carraro, L. na. A proxy-means test exercise for the selection of beneficiaries of poverty targeted programs in Mongolia. World Bank.
- Agbor, J.A. and Price, G.N., 2014. Does Famine Matter for Aggregate Adolescent Human Capital Acquisition in Sub-Saharan Africa?. *African Development Review*, 26(3), pp.454-467.
- Mazumder, B., Almond, D., Park, K., Crimmins, E.M. and Finch, C.E., 2010. Lingering prenatal effects of the 1918 influenza pandemic on cardiovascular disease. *Journal of developmental origins of health and disease*, 1(1), pp.26-34.
- Atamanov, A., Tarsicio C., Jolliffe, D., Krayem, D., and Sayed, H., 2015. "Updating the Proxy Means Testing Formula in Lebanon" *mimeograph*
- Brown, C., Ravallion, M., and Van de Walle, D., 2018. "A poor means test? Econometric targeting in Africa." *Journal of Development Economics*
- Del Ninno, C. and Mills, B. eds., 2015. Safety nets in Africa: Effective mechanisms to reach the poor and most vulnerable. The World Bank.
- DISED (Direction de la Statistiques et des Etudes Démographiques). 2014. "Mesures de la pauvreté et des inégalités" Photocopy. Djibouti: DISED.
- DISED. 2017. EDAM4-IS. Djibouti: DISED.
- DISED. 2018. *Résultats de la Quatrième Enquête Djiboutienne Auprès de Ménages pour les Indicateurs Sociaux (EDAM4-IS)*. Djibouti city: DISED. http://www.dised.dj/Rapport1_resultats_EDAM4.pdf.
- Grosh, M. and Baker, J. 1995. Proxy means tests for targeting social programs: Simulations and speculation. Living Standards Measurement Study Working Paper No. 118. Washington, DC: World Bank.
- International Energy Agency (2012) World Energy Outlook.
- Leite, P., 2015. Short-and Long-Term Targeting in Kenya.
- Narayan, A., and Yoshida, N., 2005. Proxy means test for targeting welfare benefits in Sri Lanka. South Asia Region PREM Working Paper Series No. SASPR-7. Washington, DC: World Bank.
- Ravallion, M., Van de Walle, D. and Gautam, M., 1995. Testing a social safety net. *Journal of Public Economics*, 57(2), pp.175-199.
- Sdralevich, M. C. A., Sab, M. R., Zouhar, M. Y., & Albertin, G. (2014). *Subsidy reform in the Middle East and North Africa: Recent progress and challenges ahead*. International Monetary Fund.

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ABSTRACT

Djibouti, a low-middle income country at the horn of Africa, is undertaking commendable efforts to combat extreme poverty and early childhood development challenges faced over the past few decades which has been exacerbated by the series of droughts facing countries in the horn of Africa coupled with significant increases in costs of fuel and food since early 2000s. A key pillar of Djibouti's poverty and human development strategy has been laying the ground for a social protection system through the national expansion of the Programme National Solidarité Familiale (PNSF) and the establishment of a national social registry for targeting and referral to a number of social services. In this paper, we present new Proxy Means Test (PMT) models for targeting based on the 2017 household survey data (EDAM4). The paper finds that the developed PMT models, with separate targeting formulas for rural and urban areas, appear to perform well vis-a-vis inclusion and exclusion errors observed in similar country contexts. Ex-ante simulations also show that the planned expansion of targeted social assistance program, PNSF, using the proposed targeting approaches will result in nearly 0.7 percentage point reduction in poverty nationally and 3.4- 4.1 percentage reductions in the regions. These results reinforce the effectiveness of PMT targeting approach for social assistance programs in Djibouti when carried out in combination with geographic targeting in high-poverty districts. The results also show the relevance and effectiveness of PMT as a national targeting approach in urban regions and for an expanded national social assistance program.

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