Targeting by proxy: An assessment of targeting efficiency of the proxy means test in the Occupied Palestinian Territory

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Executive Summary

The Palestinian National Cash Transfer Program (PNCTP), managed by the Ministry of Social Development (MoSD), is the main national poverty-targeted social assistance programme ameliorating the effects of deep poverty experienced by approximately 115 thousand families in the West Bank and Gaza. The program targets households that fall below the extreme poverty line, identified primarily through a proxy-means test (PMT) formula, which is also used in determining the transfer value received by beneficiary households.

The MoSD and the World Bank have collaborated to update the PMT using the latest available PECS data from 2016/2017. This report aims to reflect on and learn from these latest efforts to revise the PMT formula with the objective of contributing towards the development of the national Social Protection system in the Palestinian territories. To that end, this report assesses the expected impacts of revising the PMT formula on targeting efficiency within the PNCTP and discuss its limitations and potential adverse incentive structure. In addition, this report explores the potential for the use of the national Multidimensional Poverty Index (MPI) in targeting of the PNCTP.

Key findings

Targeting efficiency and coverage effects

The new PMT could improve the targeting efficiency relative to the current formula, but exclusion of the deep poor remains unacceptably high. At the national level, the study found a potential reduction in exclusion errors, falling from 47.6% to 38.2% among the deep poor. Introducing new functional disability indicators is expected to reduce exclusion errors among persons with disabilities living below the deep poverty line to 35.6%, down from the estimated 47.0% when applying the current PMT. However, excluding 4 out of every 10 intended recipients by design does not qualify as a good targeting approach.

The results indicate a potential for significant variation in the rate of targeting improvement at subnational levels. In Gaza, the new PMT could reduce the rate of exclusion error among the deep poor to 32.5%, compared with 42.2% under the current formula. In contrast, the new formula offers no overall improvements in targeting errors in the West Bank, where the rate of exclusion error is estimated at 69.9% for both formulae. This is driven primarily by differences between the two regions in the prevalence of deep poverty and the rate of coverage.

The introduction of eligibility thresholds for clusters of governorates serves to reduce exclusion in West Bank and further reduce it among certain vulnerable groups. After determining household PMT scores using the new formula, eligibility is then determined using cluster-specific cut-offs rather than the single national threshold used previously. Different threshold levels are established to distribute program beneficiaries in a way that resembles the geographic distribution of deep poor in the country, ensuring a corresponding minimum number of beneficiaries in each cluster. The result is a reduction of the rate of deep poor exclusion — compared with assessing the new PMT scores with a single national threshold — in the West Bank (from 69.9% to 65.0%) and persons with disabilities nationally (further from 35.6% to 25.4%), as well as among residents of refugee camps.

Exclusion errors decreases with higher coverage rates, regardless of which PMT is applied. The analysis reveals that coverage would need to reach 40% of the entire population to reduce the rate of exclusion error of the extreme poor to less than 10%, while increasing coverage to 70% would reduce the rate of exclusion error of the extreme poor to less than 1%.

Equity and transparency concerns

The proposed proxy-means test (PMT) formula includes a significantly larger number of variables than the current formula, adding further complexity to the programme. The revision retains 18 variables, drops 13 variables, and adds a total of 40 new variables to the formula. Accordingly, the final formula consists of 58 indicators which expands the number of assets included from 9 to 14 assets, greatly expands the number of geographic identifier variables, including locality level estimates of poverty and inequality, and introduces new variables focused on functional limitations to identify whether the household contains persons with disabilities. The enlargement of the formula places additional burden on social workers and program administrators and, together with the introduction of cluster-specific thresholds, risks to further obscure program rules from the public.

The introduction of local poverty and inequality variables, as well as measures of prior social assistance receipt, raises concerns about equality of treatment. In addition to variables related to individual and household characteristics, new variables related to locality-level poverty and inequality rates impact a household's overall PMT score. Holding all else equal, a household's PMT score is lower (in favor of eligibility) in a locality with greater poverty incidence, which raises concerns of exclusion of deeply deprived households residing in localities with relatively lower poverty rates. Another variable indicating prior receipt of social assistance also impacts a household's score in favor of eligibility. The use of these variables to determine individual household PMT scores raises concerns regarding equitable treatment under program rules, as households otherwise sharing the same conditions of poverty would be differently assessed for support. Furthermore, including past dependence on social assistance within the formula threatens to deepen disparities and social exclusion of previously wrongly excluded households.

Locality level poverty and inequality rates are difficult to measure and update in a timely and reliable manner, raising concern over the transparency of their use in emergencies. Locality level poverty and inequality rates are estimated in an analytical process that utilizes census data, which are typically collected every ten years on average. It is unlikely that the data required for their reliable estimation would be readily available during an emergency, which raises questions about their utility as well as concerns over the potential for criticism by the public if they are applied in an ad-hoc manner due to the inherent lack of transparency.

Transfer values determination

The use of the PMT in defining transfer values significantly and systematically underestimates the required transfer amounts, particularly for the poorest. The poverty gap rate estimated using the PMT – which informs the transfer value - is found to be about 30% lower than the published national poverty gap rate. In addition, PMT-based estimates of the poverty gap rate – hence the transfer value - deviate the most from the actual poverty gap rate at the lowest end of the wealth spectrum, where the PMT mostly underestimates the poverty gap.

The combination of PMT errors combined with the practice of applying upper limits on the transfer values penalizes the poorest households the most. The analysis finds that applying lower limits on the transfer values (i.e. a minimum benefit) has no positive impact in defining the transfer values. However, applying upper limits to the transfer value (maximum benefit) plays a significantly detrimental role by reducing the transfer values only for the poorest of the poor. The PMT errors together with the impact of the benefits cap produces an estimated transfer value that reflects only 20% of the actual poverty gap among the poorest 10% of the population, though this rises to 24.5% of the actual poverty gap among the remaining population under the deep poverty line.

Incentives and alternatives

Adverse incentives can be avoided by excluding labour status and asset ownership from the targeting formula, all while improving efficiency. The analysis simulates the impacts of increasing the prevalence of errors in the data belying the PMT. The simulation analysis concludes that exclusion errors can fall in the West Bank when data is wrongly recorded for variables that reflect labour status and asset ownership. The report argues that excluding employment indicators from the targeting formula could minimize the possibility of disincentivizing formalization of the workforce while potentially improving targeting performance.

The analysis finds that the use of the Multidimensional Poverty Index (MPI) to target the PNCTP does not significantly improve targeting efficiency, neither from the perspective of targeting deep monetary poverty nor from the perspective of utilizing a proxy-MPI measure to target multidimensional poverty. In addition, the results indicate that coverage of specific vulnerable groups such as the elderly persons, children and persons with disabilities does not vary significantly between a PMT-targeted program and an MPI-targeted program.

Recommendations

Recommendations included in this report fall under two broad categories. First are *recommendations for immediate consideration* that pertain specifically to the PMT formula and its application within the PNCTP. Second are *system-wide recommendations* that pertain to the next steps necessary for the development of the concept of means testing within the national social protection system and how and when it should be applied.

System-wide recommendations

- **The Palestinian Authority should prioritize efforts to gradually expand coverage of the social assistance beyond current levels.** While the new PMT formula is an improvement from the old in terms of reducing exclusion errors, the analysis in this report indicates that these improvements remain marginal and that the low rate of coverage curtails the possibility of any significant reduction in exclusion errors.

- **International stakeholders are recommended to combine efforts to achieve greater budgetary allocations hence greater coverage for the PNCTP and other inclusive life-cycle based social assistance schemes.** The effectiveness of social assistance in combating and alleviating poverty and vulnerability is significantly impaired by the inadequately low rates of coverage and transfer values, therefore further investment to fine tune technical aspects of the PNCTP such as targeting are unlikely to produce significant improvements to the PNCTP until the issue of inadequately low rates of coverage is systematically addressed.

- **Increase transparency with the public and reduce complexity of targeting procedures.** The revised PMT formula includes many more variables than the current version, adding further complexity to the programme and places additional burden on social workers and program administrators. Additionally, the current practice of maintaining the secrecy of the PMT formula is antithetical to the concept of transparency in public administration and cannot truly serve the purpose of minimizing any adverse incentives caused by its publication.

- **In light of the above, the MoSD should consider more transparent and rights-based and inclusive approaches** for its social assistance programmes, at least for particularly vulnerable categories and advance with building **a national social protection floor** in line with the ILO Recommendation 202[1].

Recommendations for immediate consideration

- **Maintain flexibility in the design and implementation of the PMT.** It is important that flexibility is maintained that allows ongoing refinement of the PMT formula and prevents long periods of time to elapse between different versions. This also relates to the integration of the PMT within broader Management Information Systems such as the social registry where it is recommended that they are designed in a fashion that provides the flexibility to easily amend the model parameters.

- **Remove indicators with the most harmful potential disincentives from the PMT.** The benefits of narrow targeting should be weighed against its potential drawbacks, including possible adverse incentives to formal employment and the subsequent curtailment of protections to workers through future contributory social insurance mechanisms. Similarly, the inclusion of asset ownership indicators in the formula disincentivizes proper declaration and legal registration of these assets. Results from this analysis indicate that it is possible to exclude employment and asset ownership indicators from the formula without sacrificing targeting efficiency. In fact, the analysis indicates that these indicators are most likely to contribute to exclusion errors and that excluding them from the equation could improve targeting efficiency.

- **Refrain from using the PMT to define transfer values received by targeted households.** Defining transfer values based upon the poverty gap estimated using the PMT formula introduces errors to the program that curtail the ability to achieve the objective of halving the poverty gap of PNCTP beneficiaries. When combined with the practice of minimum and maximum limits on the transfer values, the poorest households are found to receive a smaller proportion of their actual poverty gap than those just under the deep poverty line. Instead, transfer values could be guided by the average national or subnational poverty gap rates or by other benchmarks such as minimum wage legislation.

- **Strengthen the grievance redress mechanism and the role of social workers.** Given the high likelihood for exclusion errors, particularly in the West Bank where the deep poverty rate is relatively lower than the Gaza Strip, the role of social workers becomes more important in reducing exclusion and inequity caused by the targeting tool.

[1] International Labour Organization (ILO). 100 years of social protection: The road to universal social protection systems and floors: Volume I: 50 country cases / International Labour Office – Geneva: ILO, 2019. https://www.ilo.org/wcmsp5/groups/public/---ed_protect/---soc_sec/documents/publication/wcms_669790.pdf

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Acknowledgments

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1. Introduction

The Palestinian National Cash Transfer Program (PNCTP) is the main national social assistance programme implemented by the Ministry of Social Development (MoSD). The PNCTP is poverty targeted and aims to enhance the ability of approximately 115 thousand families in the West Bank and the Gaza Strip to meet their basic needs.

PNCTP target beneficiaries are households that fall below the extreme poverty line, as well as marginalized households that fall between the national and extreme poverty lines – specifically those that include persons with disabilities, elderly persons, orphans, people with chronic diseases or female headed households. Targeting is achieved primarily through a Proxy Means Test (PMT), which is utilized to rank records within the MoSD database from poorest to wealthiest in order to prioritize assistance to the poorest applicants in line with available financial resources. In addition, the PMT is utilized to determine the transfer value received by beneficiary households, which is set equal to the amount required to reduce the estimated poverty gap by 50% (i.e. the MoSD set the transfer value equal to half the difference between the national poverty line and the PMT).

The PMT formula currently utilized by the MoSD was developed with the assistance of the World Bank based upon the 2011 Palestine Expenditure and Consumption Survey (PECS) and consists of several indicators capturing the demographic, employment, asset ownership and dwelling conditions of applicant households. The data from applicants are collected through an initial interview then verified through field visits by MoSD social workers. While the PMT formula is the main tool utilized in determining eligibility, the PNCTP may also rely upon a collection of local level referral networks as well as the Social Workers to extend coverage to households that may be overlooked or erroneously excluded by the PMT formula (REACH, 2019). However, it is unclear what proportion of the PNCTP beneficiaries are selected by these means.

Previous assessments and reviews of the PNCTP and Social Protection programs of the Palestinian Authority provide mixed messages regarding the accuracy of PNCTP targeting. A World Bank targeting assessment of the Cash Transfer Program (World Bank, 2012) asserts that 70% of cases assessed as extremely poor by the PMT formula were in fact among the poorest decile nationally and claims the Cash Transfer Program to be “among the world’s best targeted programs” (pg. 23, ibid). In contrast, a recent ILO analysis found that 56% of intended beneficiaries were excluded due to targeting errors (ILO, 2020). More qualitative assessments also differ in their diagnosis, with some finding the PNCTP “exceptional […] in terms of its poverty targeting” (pg. 317, Jones and Abu Hamad, 2021) while other assessments (REACH, 2019) decry the “Black Box” nature of the PMT formula used in the PNCTP, claiming that it is “overly technical and formulaic” (pg. 13, ibid) and cites anecdotal evidence that the PNCTP wrongly excludes deserving applicants as a result of relying upon the PMT formula.

In a recent collaboration, the MoSD and the World Bank updated the PMT formula using the latest available PECS data from 2016/2017. Given the considerable lapse of time since the development of the PMT formula currently applied by the PNCTP, this effort to revise the old PMT formula is a step in the development of the PNCTP. This report aims to reflect on and learn from these latest efforts to revise the PMT formula with the objective of contributing towards the development of the national Social Protection system in the Palestinian territories. To that end, this report assesses the expected impacts of revising the PMT formula on targeting efficiency within the PNCTP and discuss its limitations and potential adverse incentive structure. In addition, this report explores the potential for the use of the nationally approved Multidimensional Poverty Index (MPI) in targeting of the PNCTP.

2. Comparing the old and new PMT formulae

The current PMT formula (referred to here as the 2010 PMT) utilized a total of 31 variables including indicators on conditions of household dwelling and asset ownership as well as socio-economic, demographic, geographic and labour market indicators. In contrast, the proposed PMT formula (referred to here as the 2020 PMT) utilizes a total of 58 indicators. The 2020 PMT formula retained 18 variables from the 2010 PMT, dropped 13 variables, and added a total of 40 new variables.

The 2020 PMT expands the number of assets considered from 9 to 14 assets and greatly expands the number of geographic identifier variables to account for all governorates and the type of environment (urban/rural). In contrast, the 2010 PMT included only 2 geographic identifier variables (West Bank/Gaza Strip and urban/rural).

Furthermore, the 2020 PMT introduces new variables focused on functional limitations to identify whether the household contains persons with disabilities as well as locality level estimates of poverty and inequality produced through the small area estimation methodology linking the 2016/2017 PECS and 2017 Census. The latter is apparently an attempt to improve PMT targeting efficiency when responding to acute shocks in an approach referred to as PMTplus. This approach incorporates information on the impact of shocks on households by using panel data in the construction of the PMT, or in the absence of panel data, by including local level information on shocks in the PMT[2].

Table 1: Number of variables by category - 2010 & 2020 PMT

Category	PMT 2010	PMT 2020
Dwelling	5	5
Demographic	8	7
Socio-economic (Household)	4	7
Socio-economic (Aggregate)	0	2
Labour Market	3	4
Health (disability)	0	2
Asset Ownership	9	14
Geographic	2	17

In addition, important changes have been introduced to the way the formula is applied in the determination of eligibility for the PNCTP. The current approach compares the estimated household level PMT with the national extreme poverty line regardless of the geographic location of the applicants' domicile. However, in line with the expansion of the number of geographic identifier variables in the model, the proposed eligibility determination method utilizes thresholds for specific clusters of governorates reflecting the maximum observed PMT score for those living in deep poverty as estimated using the 2020 PMT.

[2] Refer to Mills, del Ninno and Leite (2015) for a description of the PMTplus approach

2.1 Operational feasibility of the PMT

The expansion of the PMT 18 to 40 variables raises concerns about the feasibility of collecting the data to perform the PMT. Mills, del Ninno and Leite (2015) identify three criteria that should guide the construction of a PMT formula, including: (1) Data availability, (2) Easily verifiable and readily observable variables and (3) high correlation with the indicator of household well-being. The following text assesses the 2020 PMT against these criteria.

(1) Data availability

This criterion pertains to the availability of data that may be included as explanatory (independent) variables in the estimation of the regression coefficients. This may contain data from household surveys, but also augmented by data from administrative or other forms of aggregate data. The 2020 PMT, which utilizes the 2016/2017 PECS survey data, also incorporates external data on locality level poverty headcount ratio and Gini index. This data was generated in an application of a Small Area Estimate exercise, which typically combines a household budget survey and a census to estimate poverty headcount and other indicators at low levels of geographic disaggregation[3].

Therefore, the 2020 PMT benefits from high quality, nationally representative data and augmented with relevant external data. However, the fact that the estimates are built using outdated data is a cause for concern. Existing evidence shows that that lags in implementation of the PMT increase targeting errors and reduces overall impacts of the transfer (Brown, Ravallion and van de Walle, 2018). Previous publications indicate that the 2010 PMT had a 52% exclusion error when it was first applied, but this rate increased to 56% by 2017 (ILO, 2020).

(2) Easily verifiable and readily observable variables

This criterion refers to the ease with which the data necessary to estimate the PMT is readily observable and verifiable by the program administrators in order to minimize incentives for households to provide incorrect information to increase their chances of receiving assistance. Table 2 provides an assessment of the degree to which the variables included in the 2020 PMT formula are readily observable or otherwise verifiable. While the classifications included in the table are a subjective assessment, they are informed by either the possibility of it being observed directly by PNCTP field staff or independent verified by external data sources. For example, a visit to the dwelling would conclusively verify the number of rooms in the dwelling, there is no national illiteracy registry to verify if the head of household can read or write.

Most concerning is the aggregate socio-economic indicators category. These indicators, which are locality level poverty and inequality measures, are difficult to measure and even more difficult to update in a localized manner, which brings into question the decision to incorporate these variables within the PMT.

There are also some concerns in relation to the PMTPlus approach. Admittedly, it does seem appealing to be able to simply "update" the local poverty and inequality measures in order to expand eligibility to emergency social assistance in the event of a localized humanitarian emergency, which is a common occurrence in the West Bank and Gaza Strip. However, the process of updating these measures in practice would be anything but simple. Changing a data source or methodology almost certainly leads to variances in poverty estimates and utilizing the coefficients of the small area estimates for poverty and inequality to respond to a shock will almost certainly require applying new methods to estimate poverty and/or new data sources.

[3] For additional information on this methodology, please refer to Atamanov and Palaniswamy (2019)

Therefore, applying this approach to expand eligibility to emergency social assistance will not be a straightforward process, potentially opening the door for criticism by the public due to the inherent lack of transparency and the appearance of manipulating coverage.

Table 2: Assessment of verifiability of 2020 PMT variables

Category	Observable & Verifiable?
Dwelling	Yes
Demographic	Yes
Socio-economic (Household)	Partial
Socio-economic (Aggregate)	No
Labour market	No
Health	Yes
Asset Ownership	Partial
Geographic	Yes

Additionally, it is evident that the targeting mechanism is not the main obstacle for the PNCTP to expand coverage at a local level. Rather, the main obstacle is the extremely limited, inadequate financial allocations to the PNCTP. Expanding coverage in a locality does not require an "objective" method to determine eligibility, it requires the determination of the resources available for an expansion of the PNCTP, since experience shows that the level of need is far more likely to exceed resource allocations.

(3) High correlation of explanatory variables with the indicator of household well-being

This is a technical criterion that refers to the notion that building a PMT formula should be a pragmatic exercise that endeavors to maximize the accuracy of prediction rather than generating unbiased structural parameters. In other words, the choice of explanatory (independent) variables need not be informed by a sound, structural economic model as the objective is to produce the most accurate prediction of wellbeing, though "not to generate unbiased structural parameter estimates" (pg. 29, Mills, del Ninno and Leite, 2015). The authors' intention behind this criterion is to provide analysts constructing a PMT formula some leeway in the choice of independent variables or perhaps to tolerate biases in individual parameters due to violations to Ordinary Least Squares (OLS) assumptions as long as the resulting formula produces the most accurate prediction of wellbeing that is possible with the data.

However, no evidence exists in Palestine, or any other context, that dispels the notion that biased parameters contribute to targeting errors and it is not clear how tolerating biases in parameters would improve the accuracy of prediction. For example, including the two variables discussed earlier, locality level poverty and inequality, could violate the OLS assumption of no multicollinearity. Multicollinearity occurs when two of the explanatory variables are highly correlated, and clearly, poverty and inequality are highly correlated. Although, this is not such an egregious violation of OLS assumptions as multicollinearity typically would not bias parameters, only inflate their variance, which may lead analysts to wrongly determine that the parameters are not statistically significant.

However, it is very likely that the parameters of the PMT model are affected by endogeneity, which occurs when an independent (explanatory) variable is correlated with the error term.

Endogeneity introduces bias in the estimated parameters as they fail to account for the fact that the dependent variable and some of the independent variables are simultaneously determined.

Indeed, it is evident that variables such as locality level poverty headcount ratio or the variable depicting whether social assistance is the main income source for the household are very likely to be simultaneously determined with the household welfare level (the dependent variable). Available literature on the construction and utilization of proxy means testing often dismisses endogeneity induced biases to the OLS parameters as "not a concern" (Mills, del Ninno and Leite, 2015. pp. 48). However, given what is known about the sizeable targeting errors resulting from the PMT approach (see for example: Brown, Ravallion and van de Walle, 2018) it is surprising that no publications could be found that examine the question of whether endogeneity-induced parameter bias is a driver of targeting errors and is therefore a line of questioning worthy of further research.

2.2 Equity implications of the PMT

Pursuing poverty targeting in social assistance is often advocated for on the grounds of ensuring greater equity in access to opportunities for the poorest members of society. However, targeting errors that are introduced by flaws in the design of the targeting mechanism can be critiqued on equity grounds as well. The concept of horizontal equity is particularly relevant in this as it refers to equitable treatment of all those that share the same conditions (Hanna & Olken, 2018).

Horizontal equity does not hold in the presence of exclusion errors. Indeed, violating horizontal equity is a matter of course when applying any PMT formula. If it is argued that the variables included in the PMT are predictors of household welfare and deprivation levels, then it can be argued that the application of the geographic explanatory variables as well as other binary explanatory variables implicitly lead to violations of horizontal equity. To illustrate this point, consider as an example two theoretical households – Household A and Household B. Assume that Household A and B share the same exact characteristics: they share the same household size with the same age and gender composition, same exact number of unemployed adults with the exact same dwelling characteristics and identical asset ownership profile. Logically, one would expect these two households would receive the same PMT score and therefore have equal likelihood of being enrolled within the PNCTP. However, if – for example – Household A resides in Jenin while Household B resides in Tubas (where poverty rates are higher than in Jenin), the PMT for Household A will automatically be higher and thus give it a lower chance of being enrolled within the PNCTP than Household B despite having identical characteristics.

Referring again to the same example of Households A and B, but in this case assume that both households reside in the same location and the only difference between them is the fact that Household A relies upon social assistance as the main income source while Household B has not received social assistance. Since the variable depicting whether social assistance is the main income source is included within the PMT and has a negative weight means that Household A has a higher chance of being enrolled within the PNCTP than Household B. If both households are poor households and share the same exact characteristics and both should – in theory – receive PNCTP support, then excluding household B on the basis of this variable is especially difficult to explain. In effect, this is exclusion error that is perpetrated by previous exclusion error, thus threatening to create a class of chronically excluded poor households.

The same concerns apply to the locality level poverty and inequality indicators. Using the same example of the identical Households A and B while allowing only the locality poverty rates to vary between them helps illustrate this point. If both households are completely identical on all parameters except locality level poverty rates, then the wrongly excluded household becomes the poorer household not only because they fail to secure a social assistance income, but also because they would experience deeper relative poverty – relative both to the included household as well as to other households in their immediate environment. In effect, the exclusion of equally poor households as a result of PMT errors serves to deepen relative poverty of the excluded households, contributing to further social exclusion.

2.3 Incentive structure of the PMT

It is standard practice to keep the PMT formula a secret to reduce opportunities for corruption and clientelism in its administration (REACH, 2019). It is also kept secret to minimize adverse incentives and distortionary effects of targeting (Brown, Ravallion and van de Walle, 2018).

There is a considerable body of evidence from a variety of contexts on the distortionary effect of means tested transfer income. In developed countries, much of the existing evidence focuses on labour market impacts of the effective marginal tax rate imposed by the phase-out of the transfers due to means testing (Hoynes & Patel, 2015). In the United States, concern over reduced labour supply as a result of the implicit tax rates caused by the phasing out program benefits for higher income earners fueled a wave of welfare reform processes in the mid 1990's resulting the introduction of the Earned Income Tax Credit (EITC) scheme which aims to incentivize earning income through work by providing a negative marginal income tax rate for the poorest income earners. This model is found in a number of countries and promising experiments were recently conducted in China that present unambiguously strong evidence that EITC increases labour supply at the extensive and intensive margins and increases household earnings and expenditures (Gan et al., 2020).

Published literature from developing country contexts fails to show systematic evidence that the income effects of cash transfers lead to reduced labour supply (Banerjee et al., 2017). There is also some published literature considering the distortionary impacts of proxy means testing targeting on labour supply and asset ownership. Interestingly, some have argued that while proxy means testing could reduce labour supply for actual beneficiaries, the overall effects are not immediately visible or easily measurable due to the presence of targeting errors (Hanna & Olken, 2018).

Recent research on the distortionary impacts of proxy means testing in the context of Indonesia shows that PMT-surveyed households are aware of the incentive structure of the list of questions included in the PMT, leading to future under-reporting of asset ownership (Banerjee et al., 2020). This confirms evidence from Britain suggesting that means testing mechanisms that utilize information on asset ownership effectively place an implicit tax on asset ownership and has been shown to lead to underreporting of asset ownership by potential social assistance beneficiaries (Hanna & Olken, 2018).

The same considerations are also relevant for the application of the PMT in Palestine. While the PMT formula is kept secret and applicants do not know the specific weights for each variable, it is hard to imagine that an applicant to the PNCTP is simply not aware of the implications of being asked about the number of employed individuals in the household, or whether they were landowners.

Therefore, from a self-declaration perspective, it is likely that applying proxy means testing within the PNCTP bears influence on whether individuals within applicant households declare being employed. Although this may not have an appreciable impact on extensive labour supply, it is likely to disincentivize formalization of the workforce and thus negatively impact worker protections and access to employment based social and health insurance as well as general fiscal sustainability due to potential foregone income tax revenue.

Similarly, the inclusion of asset ownership indicators in the formula serves as an implicit tax on the assets. Evidence from other contexts shows that households are aware of the implied asset tax (Banerjee et al., 2020) raising concerns over the disincentivizes to proper declaration and possibly legal registration of these assets.

2.4 Targeting errors at national and subnational levels

Assessing targeting performance of the 2020 PMT is performed by considering exclusion error at the national and subnational levels. Targeting errors are often measured in terms of exclusion and inclusion error rates. Exclusion error refers to the proportion of intended recipients that are excluded as a result of being classified wrongly by the PMT formula and inclusion errors refers to the proportion of nonpoor cases from the total number of cases selected for inclusion by the PMT. Exclusion and inclusion errors are typically equal when coverage is set equal to the (deep) poverty rate but can vary depending on the coverage target.

Table 3: Simulated deep poverty targeting errors* for the old (2010) and new (2020) PMT

	PMT 2010	PMT 2020	% Change
National	47.6%	38.2%	-19.7%
West Bank	69.9%	69.9%	0.0%
Gaza Strip	42.2%	32.5%	-23.0%
Urban	46.9%	38.0%	-19.0%
Rural	56.9%	55.4%	-2.6%
Refugee camp	43.6%	35.4%	-18.6%
Males	47.1%	38.3%	-18.5%
Females	47.0%	37.5%	-20.3%
Elderly	54.1%	43.5%	-19.7%
Elderly-Males	46.8%	39.8%	-14.9%
Elderly-Females	55.9%	46.0%	-17.7%
Children	46.8%	37.7%	-19.4%
Children-Males	45.8%	38.0%	-17.0%
Children-Females	46.2%	39.3%	-15.0%
Disabled	47.0%	35.6%	-24.1%
Disabled-Males	46.7%	37.2%	-20.3%
Disabled-Females	49.6%	30.5%	-38.6%
Working age Adults (18-64)	47.6%	37.8%	-20.6%
Working age Adults Males (18-64)	47.8%	39.1%	-18.3%
Working age Adults Females (18-64)	47.4%	37.2%	-21.5%
Working age disabled adults (18-64)	49.8%	38.0%	-23.7%
Working age able-bodied adults (18-64)	47.2%	37.6%	-20.3%
Working age Employed adults (18-64)	55.2%	46.5%	-15.8%
Working age Unemployed adults (18-64)	40.6%	30.2%	-25.4%
Working age Out of labour force adults (18-64)	45.0%	35.5%	-21.1%

* Exclusion error and inclusion error are equal when coverage is set equal to the deep poverty rate.

Estimates of exclusion/inclusion errors from the 2010 PMT and 2020 PMT are presented in Table 3 as assessed against the coverage threshold at the national and subnational levels. The coverage threshold applied in this instance is the proportion of the population living below the deep poverty line within each category. In other words, in this analysis the PMT is utilized to rank all households from the poorest to the wealthiest and those selected for inclusion are those at or below the x^{th} percentile of the PMT distribution, where x refers to the proportion of the population experiencing deep poverty[4] at the national level and within each of the subnational categories listed in Table 3. The subnational categories considered in this report correspond to groups that face heightened risks through the life cycle, including children, persons with disabilities, elderly persons and working age adults. All groups are further disaggregated by sex.

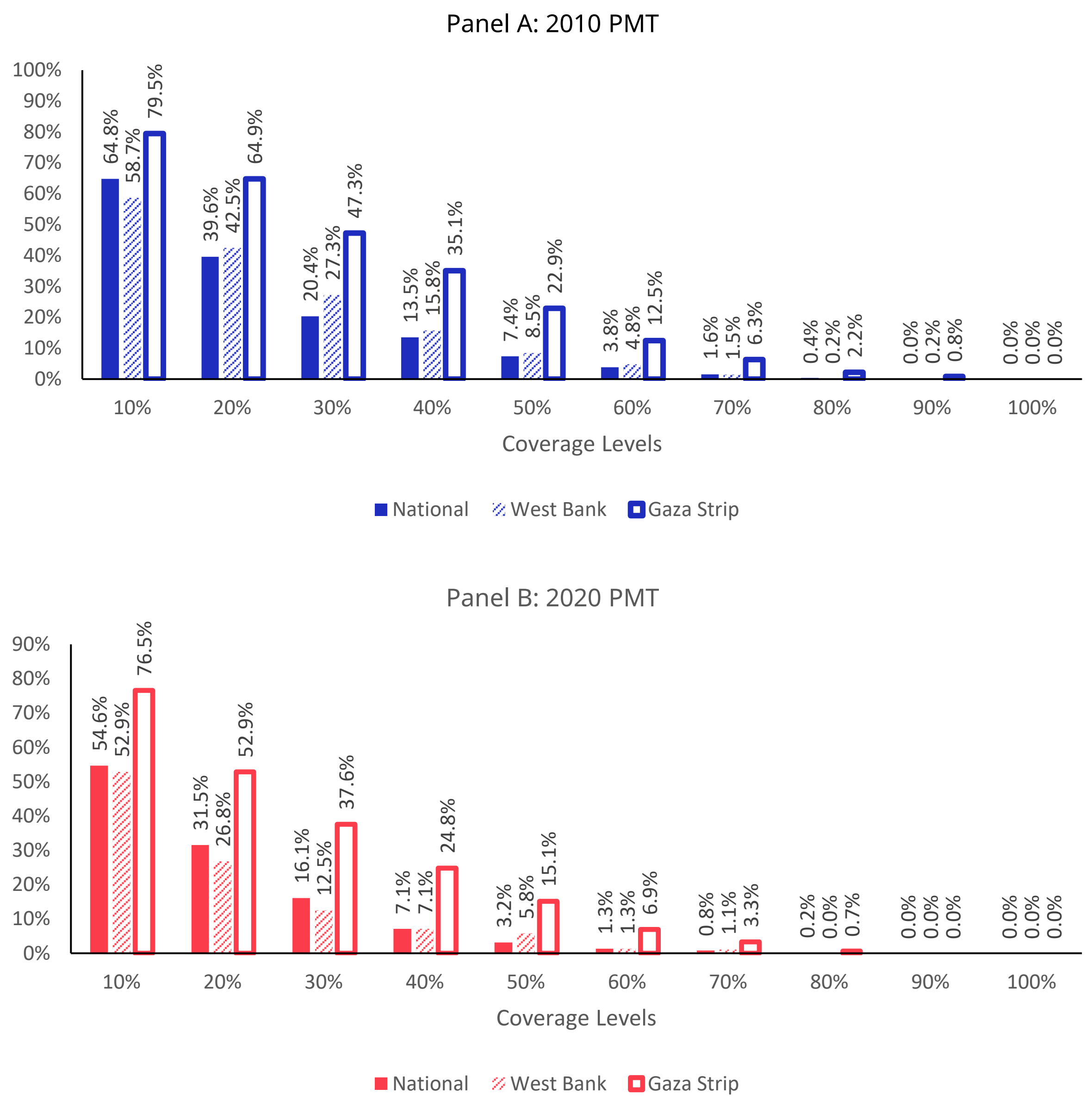
It is evident from the results listed in Table 3 that the 2020 PMT could generate significant improvements in overall targeting efficiency. At the national level, exclusion/inclusion errors could fall from 47.6% using the 2010 PMT to 38.2% using the 2020 PMT – a 19.7% reduction overall. In addition, results of this analysis point to a significant variation in the rate of potential improvement at subnational levels. Most striking is the remarkable reduction in exclusion/inclusion errors among female persons with disabilities living below the deep poverty line, which is estimated at 49.6% when applying the 2010 PMT, falling down to 30.5% when applying the 2020 PMT. In addition, working age adults (18-64 years old) experiencing deep poverty are estimated to benefit from the application of the 2020 PMT, which is assessed to reduce exclusion/inclusion errors by 25.4%.

However, at the other end of the spectrum, the results indicate that the application of the 2020 PMT offers no overall improvements in targeting errors in the West Bank, where the rate of exclusion/inclusion error is estimated at 69.9% for both the 2010 and 2020 PMT formulae when coverage is set equal to 5.8% - which is the prevalence of deep poverty in the West Bank. The results indicate a similar dynamic in rural areas which are assessed to gain minimal improvements in targeting errors as a result of applying the 2020 PMT formula. Across the board, the most that can be expected from the combination of the 2020 PMT formula and the low coverage rate of the PNCTP is that approximately 1 in 3 of those living in extreme poverty are unfairly excluded from benefitting from the PNCTP.

It is important to highlight that exclusion/inclusion errors in poverty targeted programs tend to be higher in instances of low coverage irrespective of which PMT formula is applied. This helps explain the differences in the rate of exclusion errors between the West Bank and the Gaza Strip under both the 2010 and 2020 PMT formulae. This is further illustrated in Figure 1 below, which highlights the fact that increasing coverage effectively reduces exclusion errors. Indeed, a basic fact in targeting is that increasing coverage decreases the exclusion of those living in poverty (Kidd, Gelders & Bailey-Athias, 2017), which serves as an effective argument in favour of more inclusive social protection systems. In the case of Palestine, it would require an increase in coverage to reach 40% of the whole population in order to reduce the rate of exclusion error of the extreme poor to less than 10%, and an increase in coverage to 70% in order to reduce the rate of exclusion error of the extreme poor to less than 1% using the 2020 PMT.

[4] It is estimated that 16.8% of the Palestinian population lives in deep poverty according to the 2016/2017 PECS.

Figure 1: PMT-induced exclusion of deep poor by coverage levels



2.5 Impact of cluster level cutoffs on targeting performance

In addition to the PMT formula, the recent MoSD and World Bank collaboration revised the way the PMT is applied to determine eligibility for the PNCTP. In the current system, the estimated PMT score is compared to the national deep poverty line, whereas in proposed amendment provides separate thresholds for 7 different geographic clusters. These are presented in Table 4.

Utilizing separate geographic clusters with independent cutoff lines essentially integrates geographic targeting within the PNCTP. Geographic targeting in this context allows the allocation of different coverage targets at the cluster level. The thresholds developed by the MoSD and World Bank generally reflect the maximum observed PMT score for households assessed to live below the deep poverty line according to the PMT with the exception of cluster 7 (Jerusalem-J1[5]) where a higher threshold is selected. The choice of the higher threshold for cluster 7 is apparently designed to ensure that those experiencing deep poverty in that cluster have an opportunity to benefit from the program – an opportunity they may otherwise not have due to low coverage resulting from insufficient funding of the PNCTP coupled with high demands for the PNCTP in other clusters, specifically the Gaza Strip.

Table 4: Proposed cluster specific thresholds

Cluster	Threshold (NIS)
Cluster 1: Gaza	692.64
Cluster 2: Jenin, Tubas and Jericho	775.94
Cluster 3: Qalqilia, Tulkarm and Salfit	787.24
Cluster 4: Nablus	859.23
Cluster 5: Ramallah, Jerusalem J2 and Bethlehem	825.65
Cluster 6: Hebron	774.18
Cluster 7: Jerusalem J1	1,422.68

Table 5: Distribution of deep poverty and PMT coverage with and without independent cluster thresholds

Cluster	Deep Poverty	PMT w/ national threshold	PMT selection w/ cluster thresholds
Cluster 1: Gaza	79,0%	91,0%	77,2%
Cluster 2: Jenin, Tubas and Jericho	1,8%	0,8%	1,5%
Cluster 3: Qalqilia, Tulkarm and Salfit	4,5%	2,6%	4,4%
Cluster 4: Nablus	2,9%	0,5%	2,6%
Cluster 5: Ramallah, Jerusalem J2 and Bethlehem	3,8%	1,2%	3,5%
Cluster 6: Hebron	7,7%	3,9%	6,9%
Cluster 7: Jerusalem J1	0,3%	0,0%	3,9%

As highlighted in Table 5, applying the cluster specific thresholds would have the effect of improving the geographic distribution of PMT-selected PNCTP beneficiaries to more closely resemble the distribution of the deep poor across the seven clusters. If the PMT formula was used together with a single national threshold, coverage of the PNCTP in cluster 1 (Gaza) could reach 91% of the total PNCTP beneficiaries even though only 79% of the deep poor reside in cluster 1. The implication of this is that coverage in the remaining clusters of the West Bank will

[5] Refers to localities within the Occupied Palestinian Territory controlled by the Israeli Jerusalem municipality (East Jerusalem)

be reduced to less than half of the expected coverage. Accordingly, applying the cluster specific thresholds ensures a geographic distribution of

PNCTP resources loosely in line with the distribution of deep poverty. The exception is coverage in cluster 7 (Jerusalem-J1) where the cutoff is set at a higher threshold, resulting in an expected coverage that is higher than its share of deep poverty.

The impact of applying cluster specific thresholds on exclusion error is highlighted in Table 6, which shows that the cluster specific thresholds only slightly increase exclusion errors at the national level while serving to significantly reduce exclusion errors within some subnational groups, namely residents of refugee camps (-27.3%) and Persons with Disabilities (PwD; -28.8%).

Table 6: Simulated deep poverty exclusion errors* for the new (2020) PMT with and without Cluster Cutoffs

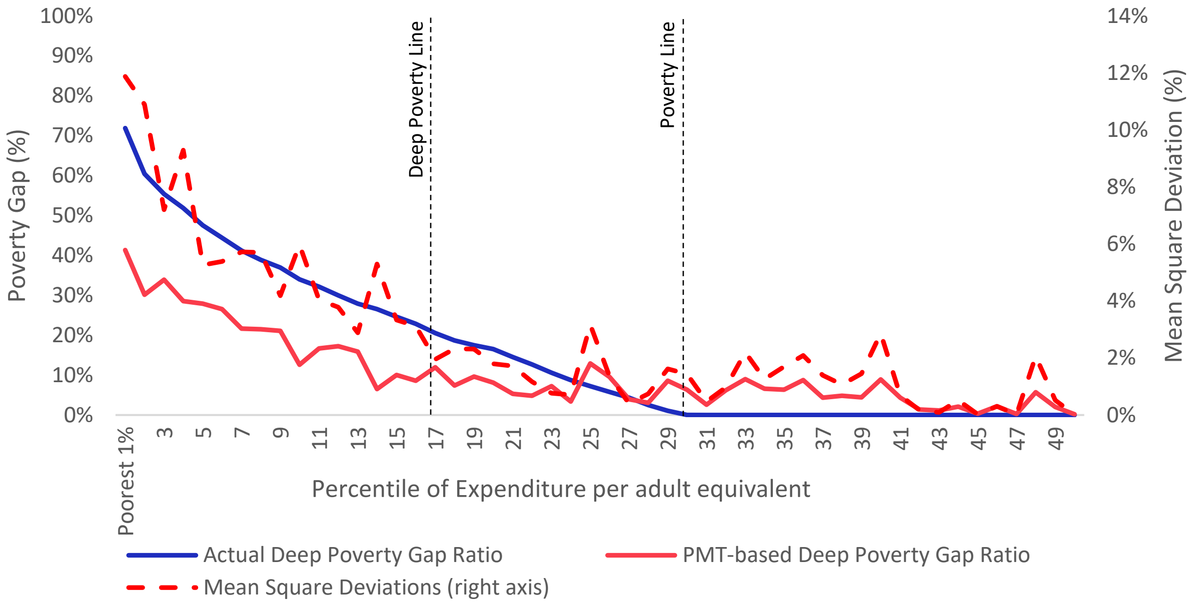
	PMT 2020	**PMT 2020 w/ Cluster cutoffs**	**% Change**
Total	38.2%	39.3%	3.0%
West Bank	69.9%	65.0%	-7.0%
Gaza Strip	32.5%	32.5%	0.0%
Urban	38.0%	39.6%	4.3%
Rural	55.4%	61.6%	11.2%
Refugee camp	35.4%	25.8%	-27.3%
Males	38.3%	38.2%	-0.3%
Females	37.5%	40.5%	7.9%
Elderly	43.5%	44.3%	2.0%
Elderly-Males	39.8%	42.1%	5.9%
Elderly-Females	46.0%	46.2%	0.4%
Children	37.7%	37.8%	0.2%
Children-Males	38.0%	35.6%	-6.2%
Children-Females	39.3%	40.0%	1.6%
Disabled	35.6%	25.4%	-28.8%
Disabled-Males	37.2%	27.5%	-26.1%
Disabled-Females	30.5%	21.9%	-28.1%
Working age Adults (18-64)	37.8%	40.7%	7.8%
Working age Adults Males (18-64)	39.1%	40.8%	4.4%
Working age Adults Females (18-64)	37.2%	40.6%	9.0%
Working age disabled adults (18-64)	38.0%	28.2%	-25.6%
Working age able-bodied adults (18-64)	37.6%	41.3%	9.8%
Working age Employed adults (18-64)	46.5%	49.8%	7.1%
Working age Unemployed adults (18-64)	30.2%	28.2%	-6.9%
Working age Out of labor force adults (18-64)	35.5%	38.5%	8.3%

* Note: since coverage is determined by cutoff rather than percentile, actual coverage can vary from the deep poverty rate, leading to different estimates for inclusion and exclusion errors. Here we focus on exclusion errors.

3. Implications of determining transfer values using the PMT

Transfer values within the PNCTP are determined as the amount required to halve the beneficiary household's poverty gap. To estimate this, the MoSD set the transfer value equal to half the difference between the national poverty line and the PMT. In addition, the MoSD applies a minimum bound of NIS 750 and a maximum bound of NIS 1,800 per quarter per household. At the aggregate level, the national poverty gap rate is reported at 7.9% (PCBS, 2017), whereas the poverty gap rate estimated using the PMT is found to be 5.5%, implying that the use of the PMT in defining transfer values underestimates the amount required to halve the beneficiary households' poverty gap.

Figure 2: Deviation between actual and PMT-based poverty gap ratio by expenditure percentile



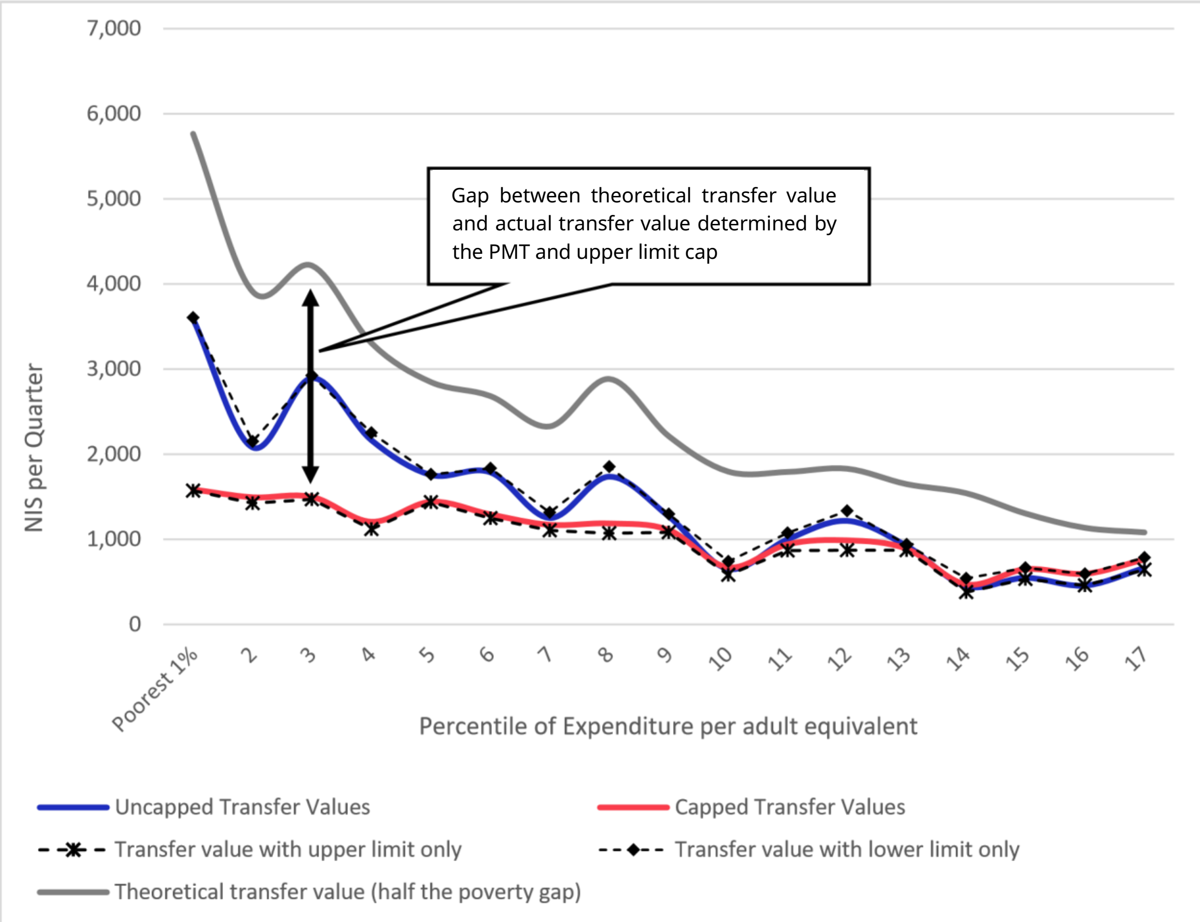
Comparing actual and PMT-based poverty gap ratios across expenditure percentiles provides an indication of the equity implications of defining transfer values based upon the PMT-based poverty gap. Figure 2 highlights the differences between the actual poverty gap rate and the PMT-based poverty gap rate along with a measure of differences between them – the Mean Squared Deviations[6] – which shows that PMT-induced errors are greatest for the poorest of the poor than for those just below the deep poverty line.

While the PMT-based deep poverty gap rate is higher for those experiencing deeper poverty, the prevalence of deviation of the PMT-based estimates from the actual deep poverty gap rate is highest at the lowest end of the wealth spectrum. In addition, practically 100% of the errors in

[6] Estimated as $\frac{\sum(x_i - y_i)^2}{n_i}$ where x_i is the actual deep poverty gap ratio, y_i is the PMT based deep poverty gap ratio and n_i is the population size for the i^{th} percentile.

the PMT-based estimates are in the direction of underestimating the poverty gap at the lowest end of the wealth distribution, whereas for those just below the deep poverty line, this rate is approximately 80%. In effect, this implies that utilizing the PMT to set the transfer value on a case-by-case basis introduces inequities that would be reduced – though not eliminated – if transfer values are determined on the basis of group averages.

Figure 3: Actual, PMT-based poverty gaps and capped nominal transfer values by expenditure percentile



In practice, cash transfer values are also subject to lower and upper limits where the minimum a beneficiary household can receive is NIS 750 and the maximum they can receive is NIS 1,800 on a quarterly basis, depending on their estimated poverty gap ratio. In theory, the lower limit could serve to increase the transfer values for households where the PMT underestimates the transfer values. In practice, however, the lower limit plays no significant role in changing the transfer values from what is estimated by the PMT formula, which is evident from Figure 3 by comparing uncapped transfer values with the trendline for transfer values with the lower limit only. In contrast, it is evident in Figure 3 that applying the upper limit plays a significantly detrimental role by reducing the transfer values only for the poorest. As a result, this analysis reveals that the combination of PMT errors and the upper bounds applied by the MoSD leads actual transfer values to represent 19.8% of the actual poverty gap among the poorest 10% of the population rising to 24.5% of the actual poverty gap among the remaining population under the deep poverty line.

4. Errors in PMT indicators: A Monte Carlo experiment

The analysis up to this point has focused on solely on theoretical errors due to the design of the PMT formula whereas actual targeting errors could differ in practice. Differences could be for the worse in the event of errors in data collection or self-reporting by applicants, or clientelism and corruption. Alternatively, differences could be for the better, particularly in instances where an effective grievance redress mechanism exists and permits overturning faulty PMT decisions.

Some evidence exists showing that errors in variables could exacerbate targeting errors in context of proxy means testing. For example, research performed on the accuracy of data collected for the PMT in Indonesia found a high prevalence of errors in data collection for specific indicators, estimating that – on average – 14.7% of the data was erroneous, rising to 37% of the data in certain localities (Kidd, Gelders & Bailey-Athias, 2017).

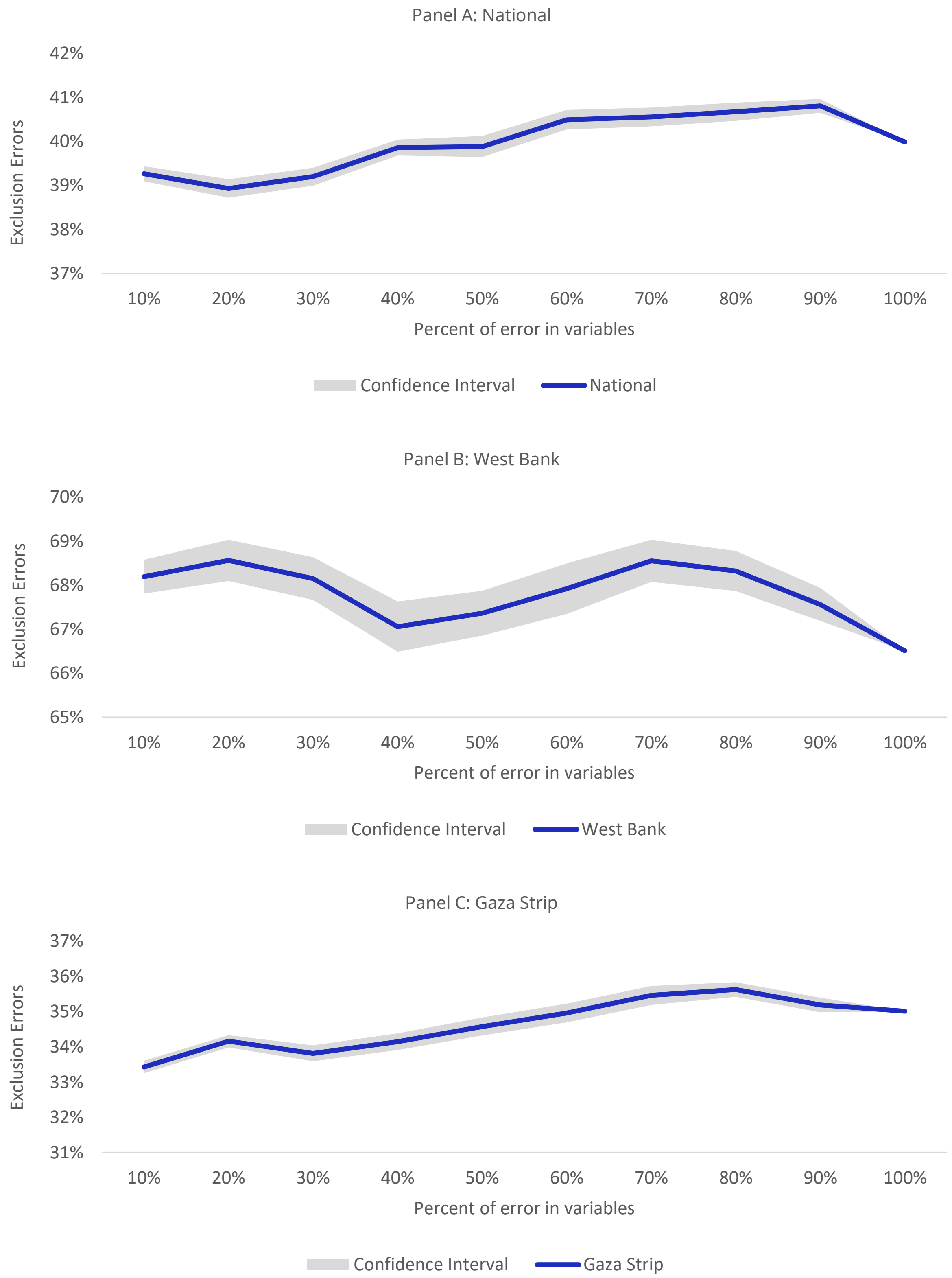
A common concern with the PMT is the notion that applicants have a clear incentive to underreport income and ownership of assets in order to increase chances of enrollment. This is a commonly cited reason against publicizing the PMT formula (Brown, Ravallion and van de Walle, 2018). Indeed, proponents of the PMT argue that it "does not discourage work or distort other incentives…because applicants do not know which variables, and their respective weights, determine the welfare or poverty level" (Mills, del Ninno and Leite, 2015, pg. 22). However, precisely this lack of transparency is a common criticism of the PMT in general (Brown, Ravallion and van de Walle, 2018) as well as in the context of the PNCTP (REACH, 2019).

In addition, recent analysis from Indonesia shows that PMT-surveyed households are attuned to incentive structure of the list of questions included in the PMT, leading to future under-reporting of asset ownership, while actual asset ownership was not altered (Banerjee et al., 2020) and can create some distortions in the labour market when employment is linked to social assistance (Camacho et al., 2014).

To assess the degree to which errors in variables could affect the targeting efficiency of the PNCTP – regardless of whether they are caused by simple error in data collection or strategic behaviour by applicants – an experiment is conducted whereby exclusion errors are estimated following the random introduction of errors to an increasing proportion of the variables within the PMT. The analysis was performed following typical Monte Carlo methods where selection of the cases where errors are introduced is performed randomly and repeatedly.

The results of this experiment are illustrated in Figure 4 depicting the Monte Carlo sample mean and confidence intervals (N=100) at the national level (Panel A) as well as separately for the West Bank (Panel B) and the Gaza Strip (Panel C). Errors were introduced randomly to a selection of variables broadly depicting asset ownership or defining the relationship of individuals within the applicant household to the labour market. These variables are: (1) employment status of the household head, (2) ratio of number of employed to the total household size, (3) number of unemployed adults in the household, (4) land ownership, (5) private car ownership, (6) smart phone ownership and (7) ownership of an Israeli cell phone number.

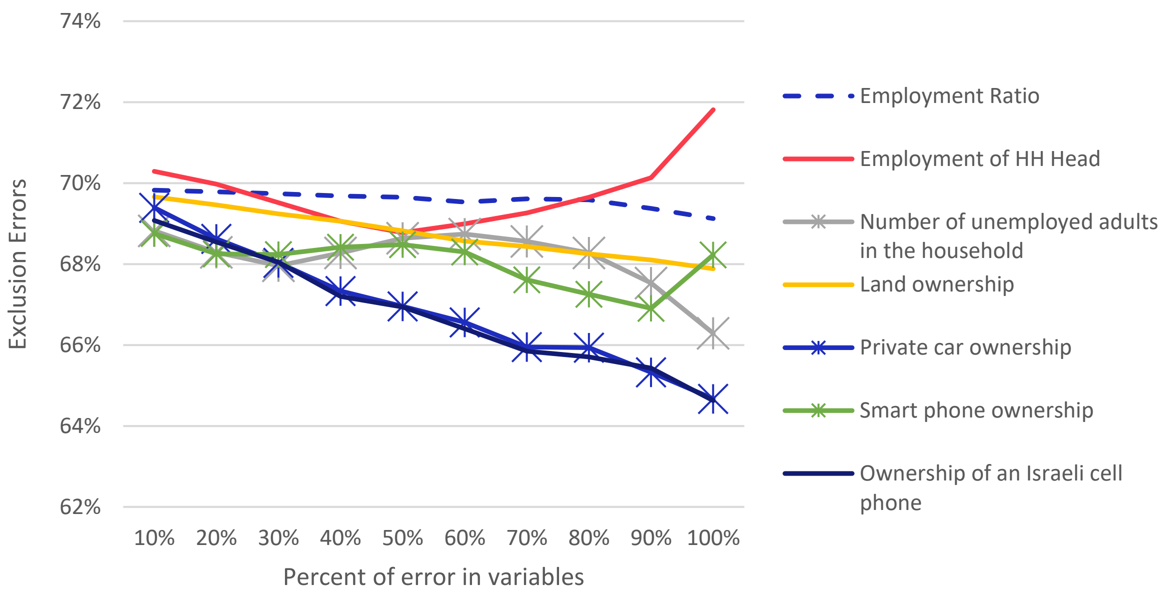
Figure 4: Simulated exclusion errors under different assumptions of errors in all selected variables



The experiment reveals dynamics whereby overall exclusion errors [7] are not necessarily increasing with the rising prevalence of errors in the underlying variables included in the PMT formula. This is particularly true for the West Bank where exclusion errors alternate between increasing and decreasing depending on the percent of errors in the selected variables. Surprisingly, exclusion error in the West Bank is lower if all the selected variables are incorrect than if they were all correctly recorded (Panel B). For the Gaza Strip, exclusion errors are generally increasing with the rising prevalence of errors in variables, although not monotonically with some reduction in targeting efficiency in the region between 20% and 30% as well as between 80% and 100% errors in variables.

To understand the driving force behind the dynamics in the West Bank, the same analysis is performed for each of the seven indicators individually. The results are presented in Figure 5 where it is illustrated that wrongly recording nearly all the considered variables improves targeting accuracy. The obvious exception is employment of the household head, where reductions in exclusion errors are maintained up to an error rate of 50% of the data, after which increases in errors would increase exclusion errors. Two variables stand out in this analysis – private car ownership and ownership of an Israeli cell phone – both of which are starkly associated with higher exclusion errors.

Figure 5: Exclusion errors in the West Bank under different assumptions of errors in individual variables



Overall, the results of this experiment indicate that it is possible to avoid loss in targeting efficiency if some variables are excluded from the targeting formula. This experiment focused on a small number of indicators that are both difficult to observe firsthand and carry significant risks of being misreported by applicants to the PNCTP. The risk of misreporting employment of a household member goes beyond the immediate implications of including a household that has an independent source of income at the expense of other households that do not. The risk

[7] With coverage set to the deep poverty rate.

extends to the possibility that including labour indicators in the targeting formula incentivizes informality in the labour market. The same applies with ownership of some forms of assets where the risk is that the targeting formula may create disincentives to the proper registration of cars, or – in the most extreme cases – registration of land ownership.

5. Opportunities for use of MPI in targeting government assistance

Within the current plans to enhance national social protection mechanisms, the MoSD intends to institute a social registry that would include data on current and potential beneficiaries which could be used to coordinate social assistance provided by various line Ministries – such as Health and Education – and which will adopt a multidimensional approach to assessing eligibility (REACH, 2019).

Soon after the Oxford Poverty and Human Development Initiative first announced the development of the Multidimensional Poverty Index (MPI; Alkire and Santos, 2010), publications emerged on multidimensional approaches to targeting cash transfers, such as the "multidimensional targeting" approach, developed by Azevedo and Robles (2013) for targeting conditional cash transfer programs in order to improve the identification of households that under-invest in human capital. However, the concept of multidimensional targeting of cash transfer beneficiaries remained largely confined to the theoretical realm, supported by a small number of publications (see for example: Duclos, Tiberti and Araar, 2018; Agurto, Calvo and Carpio, 2020).

While many anti-poverty programs target – by design – disadvantages on multiple outcomes simultaneously, particularly CCTs (Seth and Tutor, 2021) very few examples could be found where the MPI or any other measure of multidimensional poverty is an explicit inclusion criterion. This does not imply that programs targeting non-monetary – or both monetary and non-monetary – deprivations do not exist, only that the indicators of these deprivations are either considered separately for different beneficiary categories (such as low-income households with orphans or households with an unemployed household head) or that the indicators of these deprivations are combined within a single formula to estimate household welfare levels as is typically the case with PMT's generally.

The most prominent example where multidimensional poverty is explicitly applied as a targeting mechanism is the System of Identification of Social Program Beneficiaries (SISBEN) in Colombia. SISBEN is utilized in the identification of beneficiaries for various social assistance programs implemented in Columbia including *Red Unidos,* a cash assistance program targeted to the extreme poor and the *Más Familias en Acción* conditional cash transfer program targeted to poor and vulnerable households with children. SISBEN has gone through several variations where the first version applied the PMT to identify potential beneficiaries, whereas the second and third (current) version utilize the notion of multidimensional poverty to identify beneficiaries. Specifically, SISBEN utilizes a "Welfare Index" calculated using the fuzzy-set method with 24 variables reflecting four dimensions: health, education, housing, and vulnerability (ILO, 2015; Medellin and Sanchez Prada, 2015).

In Jordan, the targeting mechanism of the National Aid Fund, which is the kingdom's main cash-based safety net, is sometimes referred to as addressing "multidimensional vulnerability". However, no public information is available on the NAF targeting mechanism.

The Palestinian Central Bureau of Statistics published a report in 2020 presenting nationally approved Multidimensional Poverty Index (MPI) estimates consisting of 7 dimensions of wellbeing captured through 22 indicators (PCBS, 2020). The dimensions, indicators and weights are listed in Table 7. The analysis presented in this section assesses the merits of utilizing the MPI as a targeting mechanism for the PNCTP.

Table 7: Dimensions, indicators and weight of the national MPI

Dimension	Dimension weight	Indicator	Indicator weight
Education	0,133	School Enrolment	0,033
		Repetition	0,033
		Educational Attainment	0,033
		Quality of Education	0,033
Health	0,133	Disability Prevalence	0,033
		Chronic Disease Prevalence	0,033
		Health Insurance	0,033
		Health Access	0,033
Employment	0,133	Unemployment	0,033
		Quality of Work	0,033
		Employment Benefits	0,033
		NEET Rate	0,033
Housing Conditions	0,133	Access to Piped Water	0,033
		Disruption of Water Supply	0,033
		Ventilation	0,033
		Overcrowding	0,033
Safety and use of assets	0,133	Theft or Damage to Property	0,044
		Ownership and Use of Assets	0,044
		Interpersonal and State Violence	0,044
Personal freedom	0,133	Freedom of Movement	0,067
		Economic Freedom of Women	0,067
Monetary poverty	0,200	Monetary poverty	0,200

However, determining who is poor and therefore deserving of government assistance is a normative choice that cannot be determined by any of the individual measures – be it monetary poverty or multidimensional poverty. Therefore, assessment of the merits of utilizing the MPI as a targeting mechanism for the PNCTP follows three tracks: first through assessing ability of MPI to identify those experiencing deep poverty and second through assessing the ability of a “proxy MPI” to identify the poorest 17% of the multidimensionally poor, and finally through comparing coverage of groups of special interest such as children, elderly and disabled if eligibility were determined by the MPI with coverage if eligibility were determined by the PMT.

5.1 MPI performance in identifying deep poverty

This analysis explores the degree to which utilizing the MPI as a targeting tool might affect the targeting efficiency of the PNCTP. Given that monetary poverty is included as a dimension within the MPI, the analysis examines different possible permutations for a "Proxy" MPI, including:

- Social MPI: The Social MPI utilizes all dimensions of the national MPI excluding monetary poverty. Weights for the remaining indicators/dimensions are rescaled to reach 100%.
- MPI-PMT: The MPI-PMT utilizes the PMT vector as a proxy indicator for the "monetary poverty" dimension of the MPI by select the bottom 16.8% of the PMT distribution population.
- MPI-PMT+: The MPI-PMT+ utilizes the PMT vector and the cluster specific thresholds as a proxy indicator for the "monetary poverty" dimension of the MPI by identifying deep poverty according to the newly proposed targeting method.

Table 8: Deep monetary poverty targeting performance (exclusion error) under various MPI permutations

	Social MPI	MPI-PMT+	MPI-PMT
National	60.3%	41.0%	39.4%
West Bank	85.0%	64.7%	77.2%
Gaza Strip	53.7%	34.7%	29.3%
Urban	58.8%	41.1%	37.9%
Rural	79.9%	65.2%	68.5%
Refugee camp	55.5%	26.8%	29.5%
Males	58.5%	38.7%	37.5%
Females	62.1%	43.2%	41.3%
Elderly	79.9%	54.2%	53.2%
Elderly-Males	81.0%	50.9%	49.6%
Elderly-Females	79.0%	57.0%	56.2%
Children	56.2%	38.5%	37.0%
Children-Males	54.0%	35.6%	34.8%
Children-Females	58.3%	41.4%	39.2%
Disabled	52.5%	27.4%	25.2%
Disabled-Males	49.5%	25.6%	22.8%
Disabled-Females	57.4%	30.2%	29.1%
Working age Adults (18-64)	63.1%	42.9%	41.1%
Working age Adults Males (18-64)	61.8%	41.4%	39.8%
Working age Adults Females (18-64)	64.4%	44.3%	42.4%
Working age disabled adults (18-64)	53.8%	35.4%	26.7%
Working age-able-bodied adults (18-64)	63.5%	43.2%	41.8%
Working age-Employed adults (18-64)	67.0%	50.4%	50.8%
Working age-Unemployed adults (18-64)	58.2%	27.9%	26.1%
Working age- Out labor adults (18-64)	62.0%	41.9%	38.9%

Table 8 lists the estimates of exclusion errors from applying the various permutations of the MPI to identify deep poverty where estimates highlighted in bold text reflect categories where targeting performance meets or exceeds that achieved using the 2020 PMT with cluster cutoffs included in Table 6. It is evident from the listed results that the Social MPI performs poorly in identifying deep poverty at both national and subnational levels. The lowest estimated exclusion errors using this indicator is among disabled individuals, though this remains far higher than the errors expected from the 2020 PMT.

Although targeting performance of the MPI-PMT and the MPI-PMT+ indicators exceed that of the Social MPI, it remains generally poorer than that likely to be achieved using the 2020 PMT alone or with the cluster-specific cutoffs. Few exceptions do exist at the subnational level among particularly vulnerable groups such as children or persons with disabilities, yet the gains are so small that they do not justify the additional administrative burden associated with conducting both the MPI as well as the proxy means test, which is necessary for monetary poverty dimension within the MPI.

5.2 Proxy-MPI performance in identifying “deep” multidimensional poverty

Assessing the efficiency of targeting deep monetary poverty using a multidimensional poverty index implies an inherent preference for monetary poverty over multidimensional poverty. However, the choice of targeting for monetary poverty or multidimensional poverty is more of a policy decision than it is a technical one, and it is entirely possible and reasonable that the MoSD chose to target multidimensional poverty. Therefore, the analysis in this section presents the expected targeting errors assuming that the intended target is multidimensional poverty. Since targeting errors are fundamentally impacted by coverage levels, the analysis presented here sets coverage to reach the multidimensionally poorest 16.8% of the population, what we refer to here as “deep” multidimensional poverty.[8]

The main results of the analysis are listed in Table 9, where it is apparent that the three “Proxy” MPI measures perform only slightly better in identifying “deep” multidimensional poverty than the 2020 PMT with cluster-specific thresholds does in identifying deep monetary poverty. However, targeting errors remain high, particularly in the West Bank (over 60% exclusion error) and rural areas (approximately 50% exclusion error).

It is evident from the results that only a few of the key subnational groups stand to benefit from applying multidimensional targeting within the PNCTP. For example, exclusion errors would fall by over 20% within rural areas by applying the Social MPI. Similarly, exclusion errors among the elderly would fall by nearly 14% by applying the MPI-PMT+.

[8] “Deep” multidimensional poverty does not refer to any recognized terminology or methodology. The use of the term in the context of this paper is motivated solely by facilitating the comparative analysis with deep monetary poverty.

Table 9: "Deep" multidimensional poverty targeting performance under various MPI permutations

	PMT 2020 w/ Cluster cutoffs*	Social MPI	MPI-PMT+	MPI-PMT
National	39.3%	39.0%	37.3%	37.7%
West Bank	65.0%	64.1%	61.5%	75.3%
Gaza Strip	32.5%	31.7%	30.2%	26.8%
Urban	39.6%	40.1%	39.1%	39.1%
Rural	61.6%	48.4%	51.7%	58.1%
Refugee camp	25.8%	29.2%	21.3%	20.9%
Males	38.2%	37.4%	35.7%	35.5%
Females	40.5%	40.7%	39.0%	40.1%
Elderly	44.3%	46.0%	30.5%	36.2%
Elderly-Males	42.1%	48.3%	34.9%	39.5%
Elderly-Females	46.2%	43.9%	26.4%	33.1%
Children	37.8%	38.5%	37.3%	37.2%
Children-Males	35.6%	36.0%	34.1%	33.7%
Children-Females	40.0%	41.1%	40.5%	40.8%
Disabled	25.4%	29.0%	23.2%	25.8%
Disabled-Males	27.5%	32.3%	22.6%	24.7%
Disabled-Females	21.9%	23.7%	24.3%	27.7%
Working age Adults (18-64)	40.7%	39.5%	37.4%	38.2%
Working age Adults Males (18-64)	40.8%	38.9%	37.0%	37.1%
Working age Adults Females (18-64)	40.6%	40.1%	37.9%	39.5%
Working age disabled adults (18-64)	28.2%	30.8%	27.3%	29.6%
Working age-able-bodied adults (18-64)	41.3%	40.0%	38.0%	38.7%
Working age-Employed adults (18-64)	49.8%	44.6%	46.5%	47.8%
Working age-Unemployed adults (18-64)	28.2%	27.2%	25.0%	22.7%
Working age- Out labor adults (18-64)	38.5%	38.7%	34.4%	35.5%

* The targeting performance of this column is evaluated against deep monetary poverty whereas the remaining columns are evaluated against “deep” multidimensional poverty.

5.3 Coverage of key groups within the PNCTP

While exclusion errors are an important measure of targeting efficiency, they are only relevant in relation to the level of coverage within the PNCTP. That is why – for example – the results discussed previously in this report (see Figure 1) are unequivocally clear that the most effective way to reduce exclusion errors is to increase coverage. This conclusion is not unique to the PNCTP and is consistently drawn for several countries (Kidd, Gelders & Bailey-Athias, 2017).

Therefore, the expected rate of coverage has a more meaningful influence on the impact of the PNCTP than the choice of targeting approach. Since coverage of the PNCTP is constricted by limited fiscal space, this analysis focuses on expected coverage rates at the subnational level with particular emphasis on demographic groups that are key to the realization of a social protection floor, such as children, PwD's and elderly persons.

Table 10: Expected coverage by form of targeting

	PMT 2020 with Cluster cutoffs	Social MPI	MPI-PMT+	MPI-PMT
National	17%	17%	17%	17%
West Bank	6%	9%	6%	4%
Gaza Strip	34%	28%	33%	37%
Urban	17%	17%	17%	17%
Rural	8%	11%	8%	7%
Refugee camp	34%	24%	32%	32%
Males	17%	17%	17%	17%
Females	17%	16%	16%	16%
Elderly	16%	7%	12%	12%
Elderly-Males	16%	7%	13%	12%
Elderly-Females	16%	6%	12%	12%
Children	18%	19%	18%	18%
Children-Males	18%	19%	19%	19%
Children-Females	18%	19%	17%	18%
Disabled	31%	26%	32%	30%
Disabled-Males	34%	27%	34%	32%
Disabled-Females	28%	25%	29%	28%
Working age Adults (18-64)	16%	15%	16%	16%
Working age Adults Males (18-64)	16%	16%	16%	16%
Working age Adults Females (18-64)	16%	15%	16%	15%
Working age Disabled Adults (18-64)	35%	29%	35%	34%
Working age-Able-Bodied Adults (18-64)	16%	15%	15%	15%
Working age-Employed Adults (18-64)	10%	13%	10%	10%
Working age-Unemployed Adults (18-64)	34%	27%	34%	35%
Working age-Out Labour Adults (18-64)	19%	16%	18%	18%

One clear conclusion from the analysis is how little coverage varies with targeting approach. The exception is the Social MPI, which produces substantially different coverage rates for a few subnational groups such as the elderly (7% coverage vs 16% with the 2020 PMT with cluster cutoffs), refugee camp dwellers (24% vs 34% with the 2020 PMT with cluster cutoffs) and PwD's (26% vs 31% with the 2020 PMT with cluster cutoffs).

However, the results presented in Table 10 serve to highlight the fact that approximately 5 of every 6 children, 5 of every 6 elderly persons and 7 of every 10 persons with disabilities will not have any form of income support regardless of the form of poverty targeting, which is particularly low in a context where nearly one in every three persons lives in poverty.

6. Conclusions and recommendations

Means testing aims to direct resources towards those at the bottom of the wealth distribution and the new PMT formula is an improvement on the old formula in this regard. However, the improvement remains marginal, particularly since the main cause of exclusion error is the inadequately low coverage rate.

Narrowly targeting social assistance to those in deep poverty serves to reduce costs, but also comes with significant drawbacks – mainly reduced effectiveness in mitigating the impact of poverty and high rates of exclusion errors. This is manifested in the exclusion of 4 out of every 10 intended recipients by design with similar rates of exclusion error expected among the elderly, children and working age adults. One notable improvement resulting from the revision of the PMT is the relatively low exclusion errors among disabled persons (1 out of every 4 intended severely disabled recipients).

Including indicators of employment in the PMT formula carries the risk of disincentives to formal employment and the subsequent curtailment of protections to workers through formal, contributory social insurance mechanisms. Similarly, the inclusion of asset ownership indicators in the formula may disincentivize their proper registration. The analysis contained within this report shows that maintaining these indicators within the targeting tool contributes to exclusion errors and that targeting efficiency is not necessarily jeopardized with their exclusion. Reducing the potential disincentives from including such indicators in the targeting tool typically depends upon maintaining secrecy of the PMT formula – a practice which is contrary to basic concepts of transparency in public administration.

The revision to the PMT formula greatly increases the number of variables relative to the current version, thereby adding complexity to the programme and placing a greater burden on social workers and program administrators. The introduction of cluster-specific thresholds contributes to greater targeting efficiency, although the increased efficiency is a product of increasing coverage in areas with lower rates of poverty. However, this also lacks transparency and risks further obscuring program rules from the public.

The PNCPT also utilizes the PMT formula to estimate the transfer value at for each applicant household. However, targeting errors due to the PMT formula translate into miscalculation of transfer values and analysis contained in this report shows that this error systematically reduces the transfer value most for the poorest of the poor. This limits the PNCTPs ability to halve the poverty gap of beneficiary households.

Building upon the analysis presented above, this report presents recommendations that fall within two broad categories. First are *recommendations for immediate consideration* that pertain specifically to the PMT formula and its application within the PNCTP. Second are *system-wide recommendations* that pertain to the next steps necessary for the development of the concept of means testing within the national social protection system and how and when it should be applied.

System-wide recommendations

- **The Palestinian Authority should prioritize efforts to gradually expand coverage of the social assistance beyond current levels.** While the new PMT formula is an improvement from the old in terms of reducing exclusion errors, the analysis in this report indicates that these improvements remain marginal and that the low rate of coverage curtails the possibility of any significant reduction in exclusion errors.

- **International stakeholders are recommended to combine efforts to achieve greater budgetary allocations hence greater coverage for the PNCTP and other inclusive life-cycle based social assistance schemes.** The effectiveness of social assistance in combating and alleviating poverty and vulnerability is significantly impaired by the inadequately low rates of coverage and transfer values, therefore further investment to fine tune technical aspects of the PNCTP such as targeting are unlikely to produce significant improvements to the PNCTP until the issue of inadequately low rates of coverage is systematically addressed.

- **Increase transparency with the public and reduce complexity of targeting procedures.** The revised PMT formula includes many more variables than the current version, adding further complexity to the programme and places additional burden on social workers and program administrators. Additionally, the current practice of maintaining the secrecy of the PMT formula is antithetical to the concept of transparency in public administration and cannot truly serve the purpose of minimizing any adverse incentives caused by its publication.
- **In light of the above, the MoSD should consider more transparent and rights-based and inclusive approaches** for its social assistance programmes, at least for particularly vulnerable categories and advance with building **a national social protection floor** in line with the ILO Recommendation 202[9].

Recommendations for immediate consideration

- **Maintain flexibility in the design and implementation of the PMT.** It is important that flexibility is maintained that allows ongoing refinement of the PMT formula and prevents long periods of time to elapse between different versions. This also relates to the integration of the PMT within broader Management Information Systems such as the social registry where it is recommended that they are designed in a fashion that provides the flexibility to easily amend the model parameters.

- **Remove indicators with the most harmful potential disincentives from the PMT.** The benefits of narrow targeting should be weighed against its potential drawbacks, including possible adverse incentives to formal employment and the subsequent curtailment of protections to workers through future contributory social insurance mechanisms. Similarly, the inclusion of asset ownership indicators in the formula

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[9] International Labour Organization (ILO). 100 years of social protection: The road to universal social protection systems and floors: Volume I: 50 country cases / International Labour Office – Geneva: ILO, 2019. https://www.ilo.org/wcmsp5/groups/public/---ed_protect/--soc_sec/documents/publication/wcms_669790.pdf

disincentivizes proper declaration and legal registration of these assets. Results from this analysis indicate that it is possible to exclude employment and asset ownership indicators from the formula without sacrificing targeting efficiency. In fact, the analysis indicates that these indicators are most likely to contribute to exclusion errors and that excluding them from the equation could improve targeting efficiency.

- **Refrain from using the PMT to define transfer values received by targeted households.** Defining transfer values based upon the poverty gap estimated using the PMT formula introduces errors to the program that curtail the ability to achieve the objective of halving the poverty gap of PNCTP beneficiaries. When combined with the practice of minimum and maximum limits on the transfer values, the poorest households are found to receive a smaller proportion of their actual poverty gap than those just under the deep poverty line. Instead, transfer values could be guided by the average national or subnational poverty gap rates or by other benchmarks such as minimum wage legislation.

- **Strengthen the grievance redress mechanism and the role of social workers.** Given the high likelihood for exclusion errors, particularly in the West Bank where the deep poverty rate is relatively lower than the Gaza Strip, the role of social workers becomes more important in reducing exclusion and inequity caused by the targeting tool.

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