

How Can Vulnerable Internally Displaced Persons Be Transitioned from Humanitarian Assistance to Social Protection?

Evidence from Iraq

Chinedu Temple Obi

Lokendra Phadera

Matthew Wai-Poi

Virginia Leape

Gabrielle Fox



WORLD BANK GROUP

Poverty and Equity Global Practice

June 2022

Abstract

Aligning the short-term humanitarian assistance system with the government social protection system as a possible long-term solution for the displaced population is well discussed in the literature. However, there is limited evidence on how this alignment is applied in a real-world setting. Using field-test data, this paper documents the eligibility of the humanitarian Multi-Purpose Cash Assistance beneficiaries for the government's poverty-targeted cash transfer program in Iraq. It does so by using two possible approaches—a probabilistic pseudo-proxy-means test, which is based on a limited number of overlapping variables between the targeting models of the humanitarian and government support systems and is designed to be applied on the existing database, and a new data collection with complete sets of

variables from the targeting models of the two systems. The paper finds that a significant number of households that qualify for the humanitarian Multi-Purpose Cash Assistance program are eligible for the government's cash transfer program. While the referral accuracy of the pseudo-proxy-means tests model is high, it is likely to leave out some eligible households. In addition to identifying the cross-eligibility with certainty, collecting new data may elicit important insight related to willingness to be referred. The choice between electing to collect new data or relying on the pseudo-proxy-means tests and using existing data comes with important trade-offs and will depend on the capacity, budget, and appetite for the uncertainty of eligibility.

This paper is a product of the Poverty and Equity Global Practice. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at <http://www.worldbank.org/prwp>. The authors may be contacted at lphadera@worldbank.org, mwaipoi@worldbank.org, cobi1@worldbank.org.

The Policy Research Working Paper Series disseminates the findings of work in progress to encourage the exchange of ideas about development issues. An objective of the series is to get the findings out quickly, even if the presentations are less than fully polished. The papers carry the names of the authors and should be cited accordingly. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

How Can Vulnerable Internally Displaced Persons Be Transitioned from Humanitarian Assistance to Social Protection? Evidence from Iraq¹

Chinedu Temple Obi, Lokendra Phadera, & Matthew Wai-Poi
World Bank

Virginia Leape
Oxfam & CLCI

Gabrielle Fox
Mercy Corps & CLCI

Keywords: Social protection; Proxy-means tests; Humanitarian assistance; Cash transfer; Internally displaced persons; Iraq

JEL Classification: D04; H53; I32; I38.

¹ Acknowledgment: We acknowledge the contributions of the UK government's Foreign, Commonwealth and Development Office (FCDO), which convened the initial workshop and launched this collaborative effort. We are grateful for the guidance of the peer reviewers Sharad Alan Tandon and Phillippe George Leite. We thank Dhiraj Sharma, Rene Antonio Leon Solano, Khalid Ahmed Ali Moheydeen, Sara Hariz, and the World Bank's Social Protection Team working on Iraq for their continuous support and feedbacks. This work was undertaken under the overall guidance of Johannes G. Hoogeveen, and Ramzi Afifi Neman. This work was supported by the Iraq Reform, Recovery, and Reconstruction Fund (I3RF) trust fund. The paper is also part of the program "Building the Evidence on Protracted Forced Displacement: A Multi-Stakeholder Partnership". The program is funded by FCDO, is managed by the World Bank Group (WBG), and was established in partnership with the United Nations High Commissioner for Refugees (UNHCR). The scope of the program is to expand the global knowledge on forced displacement by funding quality research and disseminating results for the use of practitioners and policy makers. We further thank FCDO for additional funding through its Knowledge for Change (KCP) program. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors and does not necessarily reflect the views of I3RF, FCDO, the WBG or UNHCR, or those of the Executive Directors of the World Bank or the government they represent.

The following abbreviations have been applied in this paper.

PMT	Proxy Means Tests
PPMT	Pseudo Proxy Means Tests
GOI	Government of Iraq
MOLSA	Ministry of Labor and Social Affairs (of Iraq)
SSN	Social Safety Net
CCI	Cash Consortium for Iraq: The Cash Consortium for Iraq includes the International Rescue Committee, the Norwegian Refugee Council, the Danish Refugee Council, Oxfam, and Mercy Corps as the lead agency
CLCI	The Cash and Livelihoods Consortium of Iraq (formally CCI)
MPCA	Multi-Purpose Cash Assistance
MOLSA-PMT	The proxy means test adopted by the Ministry of labor and social affairs of the Government of Iraq (Government targeting model)
CLCI-PMT	The proxy means test adopted by the cash consortium for Iraq (humanitarian targeting model)
Legacy-VA	Legacy Vulnerability Assessment - The old vulnerability assessment methods used by the cash consortium of Iraq
SEVAT	Socio-Economic Vulnerability Assessment Tool. The current proxy means test of the cash consortium of Iraq
PPMT- Legacy VA	Pseudo PMT for testing the cross-eligibility between the MOLSA-PMT and Legacy-PMT
PPMT – SEVAT	Pseudo PMT for testing the cross-eligibility between MOLSA-PMT and SEVAT
CWG	Cash Working Group of Iraq
DfID	Department of International Development
MCNA	Multi-Cluster Needs Assessment

1. Introduction

The Internal displacement monitoring center estimated that as of the end of 2020, about 55 million people globally were Internally displaced persons (IDPs), and 87 percent of them were fleeing from conflict and violence.² During conflicts, IDPs, unlike refugees, take refuge within their countries but away from their homes. In theory, they are expected to be protected and assisted by their government, irrespective of the cause of the conflicts or the IDPs' affiliation, whether with the state or the insurrection. In reality, IDPs are among the most vulnerable populations in any country (World Bank, 2017). Besides the psychological trauma of crises leading to their displacement and the loss of their livelihoods and social capital, IDPs experience disproportional social and economic exclusions, struggling to access basic services and assistance. The vulnerability of IDPs is exacerbated by the fact that they may be undocumented and live close to conflict areas and, in some cases, with hosts with whom they do not share similar political, social, or cultural alignments. Therefore, there is the possibility that some IDPs may voluntarily opt-out from government social protection due to fear of persecution or lack of documentation.

The need to protect the right of IDPs and provide the assistance they need has been championed by humanitarian agencies, including the United Nations High Commissioner for Refugees (UNHCR), World Food Programme (WFP), and other international Non-Governmental Organizations (NGOs) who assist IDPs through cash transfer programs. For many IDPs, the cash transfers delivered by these agencies are the only source or make up the most significant share of their household income. However, unlike the government social safety net (SSN), the humanitarian agencies' cash transfers are usually transient, and most agencies are faced with fiscal constraints and shorter service terms. In a protracted crisis, IDPs may quickly fall back into extreme poverty with the cessation of aid, leaving a void which in many cases can only be filled by the government. More so, when the acute shocks subside, most returning IDPs come home to destroyed property, infrastructure, and lack of jobs, requiring substantial support from the government to set up their lives.

To this day, how to provide a lasting solution to the plight of IDPs in general and during their return is still a big challenge to governments, policy makers, and humanitarian agencies. At the forefront of proposed reforms for welfare improvement of IDPs is aligning the short-term humanitarian assistance system with the long-term government social protection system (Gentilini et al., 2018; UNHCR, 2019). Although there

² IDMC 2020 displacement data. See [link](#)

is a firm commitment among various actors for this linkage as enshrined in the Grand Bargain documents,³ the UN's Common Cash Platform, the Collaborative Cash Delivery Network, and the Sustainable Development Goals, how the two support systems can be aligned is still a long debate in the humanitarian field. The literature in this field has focused chiefly on the motivation, obstacles, and frameworks for integrating the two systems (Gentilini et al., 2018; Mitchell, 2018; O'Brien et al., 2018; Oxford Policy Management, 2015; Seyfert et al., 2019; UNHCR, 2019). There is, however, limited evidence on how this alignment is applied in a real-world setting.

This paper tries to fill the evidence gap in the literature by investigating a possible transition of the humanitarian caseload to the government SSN program in Iraq using field-test data. It builds on the accompanying desk review study (Phadera, et al., 2022) and documents the eligibility of the humanitarian Multi-Purpose Cash Assistance (MPCA) beneficiaries for the government's cash transfer program (CTP) delivered by the Ministry of Labour and Social Affairs (MoLSA). The recurrent and often violent security crises in Iraq have displaced and left many vulnerable. As a result of the most recent conflict, the war against the Islamic State of Iraq and the Levant (ISIL) that began in early 2014, more than 6 million people (about 15 percent of the Iraqi population) have been displaced. The MPCA programs have been instrumental in reaching the households that are most affected by the ISIL conflict and filling the void of limited coverage of the government's SSN in those areas. Recognizing the need of more permanent solution, conversations on finding a responsible pathway to align the caseload from the MPCA programs to the SSN (MoLSA's cash transfer program) began in early 2018.⁴ This provided an opportunity to explore how the potential transition may look and generate evidence. While both the humanitarian and government programs used proxy means test (PMT) for targeting, the PMT models used differ - relied on different proxies and the well-being variables were not the same. To bridge the gap, a targeting tool called pseudo-proxy means test (PPMT) was proposed through a desk review (Phadera, et al., 2022).⁵ The tool is a garden variety PMT but with the proxies limited to the overlapping variables between the targeting models of the two systems and it assesses eligibility only probabilistically. The desk study found potential for a significant number of referrals from the humanitarian database to the MoLSA program. Building on

³ The Grand Bargain is a unique agreement between some of the largest donors and humanitarian organizations who have committed to get more means into the hands of people in need and to improve the effectiveness and efficiency of the humanitarian action. See [link](#)

⁴ Social safety net (SSN), government's support program, MoLSA's cash transfer program etc. are used loosely and interchangeably to refer to the government's cash transfer program delivered by the Ministry of Social and Labour Affairs (MoLSA) throughout the paper.

⁵ The desk review or the desk review study, both refer to Phadera et al. (2022) in the paper.

the desk review, a field-test, a survey collecting complete information to construct full set of variables used in the two targeting systems, was carried out to further assess the targeting alignment.

The study presents findings from the field-test. Specifically, it examines each household's eligibility for the two programs and estimates the share of humanitarian caseload that would qualify for the MoLSA cash transfer program under different expansion scenarios. Then it evaluates the performances of the PPMT models presented in Phadera et al. (2022) in correctly identifying cross-model eligible households. Since it uses only a subset of variables from the MoLSA PMT model (full PMT), the PPMT cannot assess eligibility for the MoLSA cash transfer program with certainty. However, it can be applied directly to the existing humanitarian database and avoid the time and resources in collecting new data. It could prove to be a useful tool, particularly, when lack of budget or other circumstances (e.g., insecurity) prevent collecting new data with full PMT variables that the MoLSA uses. On the other hand, the probabilistic nature of the PPMT means some eligible households will not be referred, and some ineligible households will be. Rereferral of ineligible households could raise expectations but can create disappointment among those that are eligible but are not referred. Similarly, there is a trade-off between the probability of success and the number of referrals. Policy makers would be left with a choice between increasing the confidence level for a greater referral success rate but with leaving-out a greater share of eligible households (exclusion error) and decreasing the confidence level for a lesser exclusion error but with including a greater share of non-eligible households (inclusion error), raising budget concerns.

Consistent with the desk review, the field-test analysis finds a significant number of households that qualify for the humanitarian MPCA assistance to be eligible for the government's cash transfer program. While the referral accuracy of the PPMT models are high (low inclusion error), they are also likely to leave out a number of eligible households (high exclusion error). Following Phadera et al. (2022), the cross-referrals are examined under two vulnerability assessment models used by the MPCA program - the legacy Vulnerable Assessment model (Legacy -VA; referred to as VM in Phadera et al. (2022)) and the updated 2019 model called the Socio-Economic Vulnerability Assessment Tool (SEVAT). The analysis shows that 40 percent of the households identified as extremely vulnerable by the SEVAT model would also be considered as poor by the MoLSA PMT scoring and, thus, would be eligible for the government's cash transfer program under a scenario where the program expansion is limited to those below the national poverty line of IQD 110,000 per capita consumption per month (a medium-small program). For the same expansion, the referral rate for the Legacy-VA extreme vulnerable group would be about 20 percent. Again, as per the desk review recommendation, the PPMT performance is evaluated under two

methodologies. In the first method, using the eligibility thresholds presented in Phadera et al. (2022) as hard cutoffs, inclusion errors of the PPMT models corresponding to the SEVAT and Legacy-VA models would be 15 and 21 percent, respectively, under the high confidence level. While these errors are well below the levels observed in practice, PPMT exclusion errors would be extremely high at 95 percent for both the models. This translates into referring only 2 percent of the extremely vulnerable humanitarian beneficiaries to the government program. However, exclusion errors under the second (ranking) approach, which is likely to overcome the differences arising from survey design and other data related disparities (further discussed in analytical strategy section 3.2), would be within the acceptable level of 30 and 15 percent for the PPMT corresponding to the SEVAT and Legacy-VA models. Both models would refer about 36 percent of the extremely vulnerable households to the MoLSA program.

The choice between electing the PPMT models and collecting new data will depend on capacity, budget, and appetite for the uncertainty of eligibility but the choice comes with important trade-offs. Besides identifying the cross-eligibility with certainty, collecting new data may elicit greater insight into the possible transition. For instance, the field-test data showed that a smaller but a meaningful share of households (3 and 16 percent for SEVAT and Legacy-VA models respectively) that are deemed non-vulnerable and, hence, ineligible for any humanitarian assistance, in fact, would be eligible for the MoLSA program when applying the full-PMT. This group, otherwise, will not even be considered for the cross-eligibility assessment when relying purely on the PPMT models and the existing humanitarian database. Moreover, perceived ISIS affiliation and fear of persecution may mean some households do not want to be referred to the formal government system. One-third of the households that are eligible for the humanitarian assistance in the field-test data are unwilling to be referred to the government support. Therefore, new data collection could be a preferred choice for the policy makers. However, the door-to-door survey sweeps are expensive, time consuming, and may not be possible to implement due to security, lack of capacity or other reasons. In such case, the ranking approach of the PPMT model could serve as an acceptable alternative.

The rest of the paper is organized as follows. The next section provides the background including the collaborative initiative between various study partners. Discussion on the humanitarian and government PMT models, field-test, and the analytical approach is presented in section 3. Findings from the analysis are presented in section 4 and concluding remarks are discussed in section 5.

2. Study Background

We summarize in this section the collaborative initiative between the members of the CLCI, CWG, and the WB that led to this working paper. The accompanying policy note (Jovanovic et al., 2021) discusses the policy initiative and lessons learned from the engagement, while the desk review paper (Phadera, et al., 2022) documents the theoretical soundness and analytical procedure of the PPMT.

More than 6 million Iraqis were forcibly displaced from their homes because of the conflict with ISIS that began in 2014. With the de-escalation of the crises and gradual return to normalcy, some 4.8 million displaced persons have returned, with more than 1.2 million remaining internally displaced as of July 2021.⁶ As Iraq begins its long recovery journey, some essential services like health, education, and social protection remain out of reach of many displaced and returnees (IOM, 2019). Reintegration into the community have been difficult for many returnees with absence of livelihoods and services, lack of social cohesion, and security concerns. Access to a relevant social protection network remains a challenge for both the IDPs and the returnees due to obstacles such as complicated registration procedures, lack of documentation and inadequate assessment capacity of the authorities.

The situation resulted in the government and international community's commitments to support IDPs and returnees through long-term and large-scale plans that go beyond humanitarian assistance. From the onset of the Iraqi crises, cash assistance to Iraqi IDPs has been chiefly championed by two coordination humanitarian bodies - the CWG and CLCI, through their signature cash transfer program - the MPCA. More than 1 million IDPs in Iraq have benefited from the MPCA, and the total value of the MPCA has exceeded \$114 million (Jovanovic et al., 2021). This value, although substantial, would not be sufficient to meet the needs of all displaced persons in Iraq. Policy makers are also concerned about the well-being of IDPs with the reduction and coming cessation of this humanitarian aid.

On the other hand, the Iraqi state assists its citizens, including some IDPs, through the Public Distribution System (PDS) of food and the social safety net (SSN) that provides unconditional cash transfers to poor households. About 1.36 million households have benefited from the SSN (Jovanovic et al., 2021). As the number of beneficiaries is significantly lower than the total population of poor in Iraq, there are ethical reasons for expanding the program. Given Iraq's tight fiscal space, expanding the SSN, however, is a challenge. Currently there are more than 700,000 households, some of which are already verified as eligible, on the waitlist for the assistance. Lack of a social registry is another obstacle the program faces.

⁶ IOM DTM for Iraq. See [link](#)

On the brighter side, with support from the World Bank and other partners, the country is working to create a comprehensive, integrated, and effective SSN and with sufficient fiscal space the dedicated social protection could include the welfare and recovery of IDPs and returnees.

Plans to explore how to integrate the MPCA targeting models used by the humanitarian agencies (CLCI-PMT) and the SSN targeting model used by the Government of Iraq (MOLSA-PMT) started in 2018 through a Social Protection workshop convened by FCDO (formally DFID, with the Ministry of Labor and Social Affairs (MoLSA), the World Bank (WB), the Cash and Livelihoods Consortium for Iraq (CLCI), the CWG and key UN agencies in attendance. The workshop aimed to develop a roadmap document for the transition from MPCA to state-led SSN. Technically, it involves ways to identify beneficiaries of the MPCA caseloads eligible for assistance under the SSN. One of the initial outputs from the eligibility analysis exercise is the PPMT developed by the World Bank. PPMT is a probabilistic model that predicts the likelihood that a household eligible for MPCA would also be eligible for SSN. The PPMT results could assist the government in prioritization, either by ranking the most vulnerable households receiving humanitarian cash transfers and/or by identifying the conflict-affected areas where a larger number of IDPs receiving humanitarian cash transfers would likely be eligible for SSN assistance.

The procedure and result of applying the PPMT on two caseloads of the humanitarian data sets - the CLCI Legacy caseload and the new MPCA caseload are available in the associated desk review paper (Phadera, et al., 2022). Results from applying the PPMT models to these data sets suggest potential for both significant referral numbers and a sequenced referral strategy. To allow for budget flexibility, the desk analysis focused on the level of expansion (e.g. targeting the poorest 15, 20, etc. percent nationally) and the degree of confidence of a successful referral. However, given the small number of overlapping proxies between the MPCA and SSN targeting formula, the PPMT cross-eligibility results are probabilistic estimates.

Furthermore, the lack of trust in the government or fear of persecution, for example due to perceived ISIS affiliation or being ISIS sympathizers, may mean not all identified likely eligible households might be willing to be referred to the formal government social protection system. To confirm the promising referral percentages and to determine the proportion of the likely households who are also willing to be referred, a field test was carried out during the CLCI's assessment process in late 2020. The field survey collected information on the full set of questions required to construct both the MOLSA-PMT and the CLCI-PMT scores from the same households and their willingness to be referred to the MOLSA program.

3. Methodology

3.1. Developing the Proxy Means Test models

PMT predicts consumption using verifiable and measurable proxies (variables) closely correlated with consumption. Using data from the national household surveys, it identifies the best predictor of the welfare variables from a set of independent variables such as location, housing quality, household characteristics, and ownership of durable goods and assigns weights to each proxy. Although the two main targeting models examined in this paper - the MOLSA-PMT-model and the CLCI-PMT model are similar in adopting the PMT design, the eligibility criteria, variables, and scoring procedure differ.

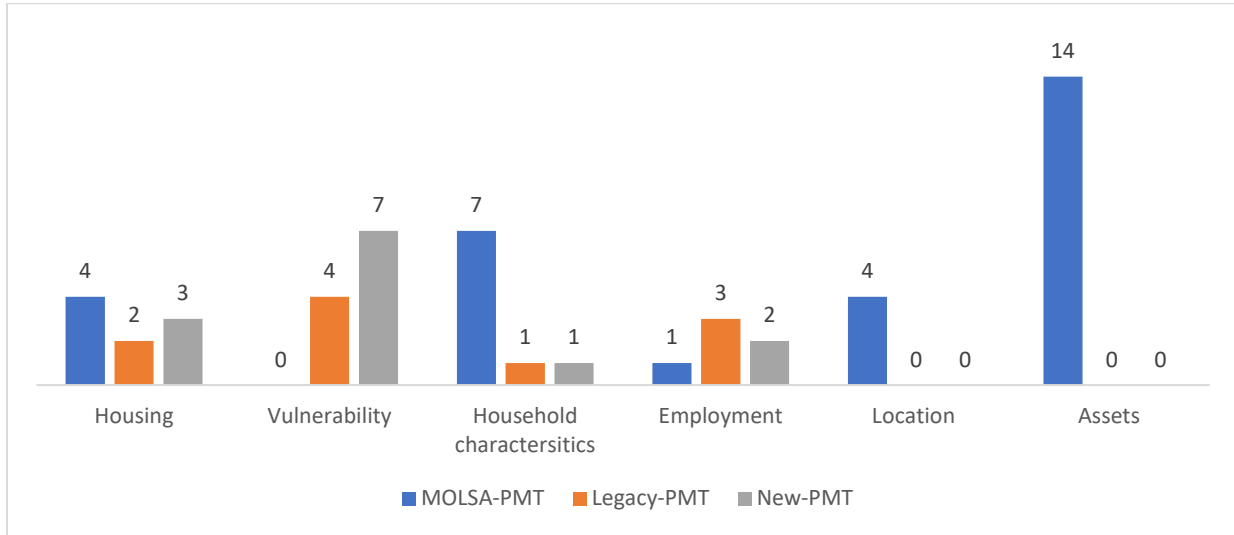
The MOLSA PMT model was developed from the 2017-2018 Rapid Welfare Monitoring Survey, also known as the Survey of Well-being via Instant and Frequent Tracking (SWIFT) (Sharma & Poi, 2019).⁷ The CLCI, however, has two PMT models, a legacy Vulnerable Assessment model (Legacy -VA) and the updated MPCA model (SEVAT). The Legacy-VA differed considerably from the MOLSA-PMT. It estimates the income-to-earnings ratio while the latter estimates household per capita consumption. The Legacy-VA uses a stepwise binary regression model to select the proxies and adopts a single model for all regions. The MOLSA-PMT, in contrast, uses continuous per capita consumption as the outcome variable in a post-Lasso procedure and has separate models for each region. The SEVAT, which replaced the Legacy-VA and uses the 2018 Multi-Cluster Needs Assessment (MCNA) survey, is more similar to the MOLSA-PMT. Both have regional models and estimate household per capita consumption per month as a dependent variable.

The variables included in the three targeting models – MoLSA, Legacy-VA, and SEVAT equally differ (Figure 1). The MOLSA-PMT variables are mostly geographic location, durable assets, housing, and other socioeconomic variables that are closely correlated to monetary poverty. Conversely, the variables included in the two CLCI-PMTs (Legacy-VA and SEVAT) are mostly coping strategies and employment, which are more likely to predict vulnerability to poverty. It should be noted that vulnerability to poverty accounts for poor households and households living on the edge of poverty (Dutta et al., 2011). Hence, it is expected that the shares of people identified by a vulnerable-to-poverty indicator could be larger than the share of households who are monetary poor (Pritchett et al., 2000). The implications for the analysis are: 1) that we may not find 100 percent cross-eligibility when matching the CLCI-PMTs with the MOLSA-

⁷ See Sharma and Wai-Poi (2019) for details.

PMT irrespective of the approach we adopt – PPMT or Full PMT. 2) the CLCI-PMTs that are more highly correlated with the MOLSA-PMT will likely show higher cross-eligibility.

Figure 1: Comparing the variables included in the targeting models for the Northern region.



The PPMT model was developed because of the incomplete overlap between the CLCI-PMTs and the MOLSA-PMT. The surveys from which the Legacy-PMT and SEVAT were produced do not have the complete set of MOLSA-PMT variables. The PPMT weights are calculated by running an ordinary least squares (OLS) regression of household per capita consumption per month on the common indicators of the humanitarian and government models. The referral accuracy of the PPMT is calculated using a probabilistic model. As with the MOLSA-PMT, the nationally representative SWIFT survey (2018) data was used to develop the PPMT and their referral cutoffs. Two sets of regional PPMT were formulated, one for the common variables between MOLSA-PMT and Legacy-PMT, and the other for the MOLSA-PMT and SEVAT.

3.2 The Field-Test Survey

The field test survey implemented a complete set of questions to construct full the three targeting models (MOLSA-PMT, Legacy-VA, and SEVAT) and, hence, the two PPMT models (PPMT-Legacy-VA and PPMT-SEVAT). The inclusion of the full set of variables helps to compare the PPMT performance with the original full PMT models. The CLCI conducted the field survey during the new round of MPCA vulnerability assessments in 2020 in areas of intervention in the Northern region of Iraq in Anbar, Diyala, Kirkuk, Ninewa, and Salah al-Din governorates. The sampling procedure mirrored the CLCI survey

approach for targeting since the survey data would be part of the regular MPCA targeting program. The CLCI adopted a census-like door-to-door house-visit approach in selected neighborhoods chosen based on reported high levels of need. Data collection was non-random, reflecting only households in neighborhoods already identified as vulnerable. The total sample size was 10,818 households. Summary statistics of the variables of interest are shown in Table 1. By design, the data comes from the North – CLCI’s area of intervention at the time – and, thus, is not nationally representative of the displaced population in Iraq. It is, however, representative of the caseload of the CLCI’s assistance and the lessons shared in the paper are highly relevant in the conflict-affected contexts with significant displaced populations and the presence of humanitarian cash transfer programs.

Table 1: Summary statistics of variables of interest (n = 10,818).

Household_characteristics	Frequency	%
Female-headed household	3042	28
The household head is disabled	1559	14
No household member worked	3745	35
The household cannot afford basic need	6680	62
The household head document is missing	1636	15
Rural households	5472	51
Lowest asset quantile	2792	26
<u>Status</u>		
Displaced (& refugee)	1388	13
Host (& remainee)	639	6
Returnee	8791	81
<u>Governorate</u>		
Anbar	2334	22
Diyala	180	2
Kirkuk	477	4
Ninawa	6113	57
Salah_al_din	1714	16
<u>Referral</u>		
Registered for government social assistance	7078	65
Registered for Minha COVID 19 program	3297	30
Willing to be referred	7278	67

3.3 Analytical strategy

The analytical strategy adopted in this paper follows a six-step procedure.

Step 1. PMT score calculation: We construct 5 PMTs and calculate the PMT scores for each household in the data. These PMTs, as highlighted above, include: 1) MOLSA-PMT score: the full official PMT scoring model which estimates household per capita consumption and determines eligibility for MOLSA social

assistance. 2) Legacy-VA score: the humanitarian scoring model used before 2018 to predict household vulnerability and determine eligibility for CLCI cash assistance. 3) SEVAT score: the humanitarian scoring model used since 2019 to predict household vulnerability and determine eligibility for CLCI cash assistance. 4) PPMT-Legacy-VA score: a model which predicts eligibility for MOLSA programs based on the common variables from the Legacy-PMT scoring model. 5) PPMT-SEVAT: a model which predicts eligibility for MOLSA programs based on the common variables from the SEVAT scoring model. The first three scoring models are the actual models used to determine MOLSA and CLCI eligibility. The two pseudo-models are used to predict likely cross-eligibility when only partial scoring information is available in humanitarian databases.

Step 2. PMT scores correlation analysis: The second step is analyzing the correlation between the PMT scores. The correlation is done using Spearman's ranked correlation to see the relationships, whether positive or negative, between the calculated PMTs (the two CLCI-PMTs and PPMTs) and the MOLSA-PMT scores. We also constructed a kernel density distribution plot to examine the relationship among the PMTs further.

Step 3. Single eligibility calculation: In step three, we identify households eligible to receive support under each of the three main PMTs; MOLSA-PMT, Legacy VA, and SEVAT, and calculate their proportion against the total sample size. Eligible households are the households whose PMT score falls below a specific cutoff determined by the relevant agency. For the MOLSA-PMT, all households below the bottom 18 percent of the PMT score are considered eligible. The bottom 18 percent of the population is the national poverty line, and it implies that this population consumes below IQD110,000 per capita per month. It should be noted that other cutoff levels, including bottom 15 percent, 20 percent, 25 percent, 30 percent, and 35 percent, are included in this paper for comparison. The Legacy-VA and SEVAT have three cutoffs that are synonymous with CLCI's three levels of vulnerability and support. For example, households with scores below the first cutoff, 4.84, in the SEVAT in Table 2, implies they consume below 70,000 IQD per person per month, identify as the most vulnerable households, and qualify to receive three cash transfers. While those between the first and the second cutoff points are eligible for two transfers and that those between the second and third are eligible for one support. Households above the third cut-off are deemed non-vulnerable and do not qualify for any support. The cutoffs and share of households eligible under each category are shown in Table 2.

Step 4. Cross-eligibility calculation: Cross-eligible households are the households who are eligible for humanitarian support (α) and also identified to be eligible for government assistance (β) under the full

official PMT. It is calculated using crosstab analysis, representing a subset of the intersection of eligibility α and β as described in Equations 1. For instance, the number of eligible beneficiaries under Legacy PMT (or SEVAT) that would qualify for government assistance under MoLSA-PMT. Since the government and humanitarian agencies have different eligibility cut-offs, selecting the best combination to calculate cross-eligibility is key as would be shown in the result section. The share of cross-eligible households can be calculated by checking within the subset of those eligible for humanitarian support who would be eligible or ineligible for government assistance.

$$\frac{\alpha \cap \beta}{\alpha} * 100 \quad \dots \dots \dots (Equation 1);$$

that is, the percentage of humanitarian beneficiaries eligible for MoLSA assistance

Where α = eligible for humanitarian transfer

β = eligible for government transfer

μ = total sample

\cap = intersection sign

Step 5. PPMT referrals and referral accuracy: This step involves calculating the share of households eligible for humanitarian support and government assistance correctly referred by the pseudo-PMT. There are two ways to predict eligibility using the PPMT scores. The first method is to use the predefined referral cut-offs identified during the PPMTs development stage; we call this the “threshold” approach. These eligibility thresholds are based on the survey-based estimates of eligibility and may or may not result in the modeled number of households being predicted eligible. The second procedure is to use the PPMT score to rank households and use a pre-set targeting rate of a group/region to determine eligibility; for example, referring households with the bottom 25 percent of the PPMT-score within a group/region; we call this the “ranking” approach (World Bank, 2012). This approach results in the “correct” number of households being determined eligible (thus satisfying budget and planning requirements) regardless of whether a particular household’s score predicts it to be eligible or not. Given significant and similar ordering of households between the PPMT and full PMT, the latter, in particular, is useful when the data on which the PPMT is devised and data on which the model are applied are different; as in the desk review paper (Phadera, et al., 2022). The PPMT’s performance can be judged using six performance indicators, and the formulae to calculate them are presented in (Phadera, et al., 2022). However, we will concentrate on the three most important indicators relevant to analysis for ease of presentation. These indicators include the referral success – the probability that a household in the humanitarian database who is eligible

for MoLSA is correctly referred by the PPMT. Referral failure – the probability that ineligible households are referred. Failure to refer – the probability that a household in the humanitarian database who is eligible for MoLSA is not referred by PPMT.

Step 6. Disaggregated analysis: The disaggregated analysis is conducted using summary statistics. In the first analysis, we calculate the share of cross eligible households across a population of interest, such as displaced and returnee households, female-headed households, households with high disability and chronic illness, households with no working members, and households in different governorates. In the second disaggregated analysis, we calculate the share of (cross) eligible households that are willing to be referred to the government support.

4. Results

4.1 The PMT score distribution

We apply the MoLSA PMT, Legacy VA, SEVAT, and the two PPMT models to the data collected from the field test. The correlation and kernel density of the PMT scores are shown in Table A1 and Figure A1 in the Annex. The MoLSA-PMT score ranged from 3.9 to 6.4, with a mean of 5, indicating that a larger share of the population lies at the right-hand (richer) side of the distribution. The MoLSA-PMT scores are expressed in a natural log and the IQD equivalent of the PMT would be calculated by an exponential function of the score, as shown in Table 2. The SEVAT score and the PPMTs show similarity in distribution with the MoLSA-PMT score. However, the Legacy-PMT has a unique distribution, ranging from 0 and 52, with 19.6 as the mean. The two PPMT distributions are wider than those of the MoLSA-PMT and SEVAT but lean towards the left-hand (poorer) side. While the SEVAT and the two PPMTs positively correlate with the MoLSA-PMT, the legacy PMT is negatively correlated with the MoLSA-PMT. This is expected as they use widely different targeting variables.

4.2 PMT cutoffs and eligibility proportion

Table 2 shows the cutoffs of each targeting model and the share of the population that are eligible under different program eligibility criteria. The result shows that in the humanitarian targeting system, more households are classified as vulnerable, as such are eligible for humanitarian support in contrast to the number of households classified as poor and eligible for social protection by the government's PMT model. For example, about 63 percent of the sample are considered vulnerable and would be eligible for either 1, 2, or 3 times of assistance using the SEVAT model, and about 60 percent would be eligible in the Legacy VA model. However, the MoLSA-PMT model classifies only 21 percent of the sample to be living

below the national poverty line of IQD 110,000 and eligible for support. Despite having the same qualification cutoffs (IQD 110,000), the difference in the estimated eligibility rates between the SEVAT and MoLSA PMT can be attributed to: (i) difference in targeting model - while the MoLSA PMT is devised to assess households' monetary poverty, the SEVAT model evaluates vulnerability, (ii) difference in the survey methodologies between the GOI's SWIFT and the CLCI's MPCA surveys – the SWIFT collected detailed household food and non-food expenditures from a nationally representative sample to estimate monetary poverty in Iraq, whereas the MPCA asked only about the total expenditure in a single question; research shows that these measures can be significantly different (Beegle et al., 2012).

Table 2: Share of households eligible in each targeting (n = 10818).

Eligible criteria	Cutoff	IDQ (Monthly per capita consumption)	Number eligible	Share of the total sample (%)
<u>SEVAT</u>				
Extreme vulnerable	<4.84	<70,000	2,921	27%
Extreme - Mid vulnerable	<4.96	<92,000	5,029	46%
All vulnerable group	<5.04	<110000	6,815	63%
Non vulnerable / not qualified	>5.04	> 110,000	4,003	37%
<u>Legacy-VA</u>				
Extreme vulnerable	from 17 - 26	Host or displaced > 3 months	4,868	45%
Extreme - Mid vulnerable	from 17 - 26	Host or displaced	6,239	58%
All vulnerable group	9 and above	Host or displaced	6,491	60%
Non vulnerable / not qualified	below 9	Host or displaced	4,327	40%
<u>MoLSA-PMT</u>				
Bottom 15% nationally	4.6	100000	2,124	20%
Bottom 18% nationally	4.7	110000	2,325	21%
Bottom 25% nationally	4.9	135000	4,356	40%
Bottom 30% nationally	4.9	140000	4,644	43%
Bottom 35% nationally	5.0	150000	5,375	50%

Note: The unit of PMT score of SEVAT is Log10, the unit for legacy VA score is an index between 0 and 50, and the unit of MoLSA is the natural log.

4.3 The referral rate using the Full PMT

The share of households referred (i.e., cross-eligible households) was analyzed using Equation 1 described in the methodology section. We are interested in calculating the proportion of households eligible (or

ineligible) for humanitarian cash transfers that also qualify for the government cash transfer using the MoLSA-MPT. The result of the different overlap possibilities is presented in Table 3, showing the cross-eligibility between different vulnerable groups in the humanitarian models (such as extremely vulnerable group - below first cut-off, extreme and mid vulnerable groups below the second cutoff, and all vulnerable groups below the third cutoff) and the different possible cutoffs for the government model (bottom 15 percent, 18 percent, 25 percent, 30 percent, 35 percent). Combining the humanitarian cutoffs with the government cutoffs gives a different proportion of overlaps. For instance, among the households categorized as extremely vulnerable by the SEVAT, 40 percent would be eligible for the government assistance under the MoLSA-PMT scoring if the government expanded the support to only those below the national poverty line i.e., those in the bottom 18 percent nationally.

If we extend the overlap analysis including the other two less but still vulnerable groups, the referral rate would reduce to 36 for the extreme and mid vulnerable groups and 32 percent when including all three vulnerable groups. Despite the decrease in share, it should be noted that the expansion of the humanitarian cutoffs increases the actual number of households referred. This is because the subset from which the overlap is calculated has now increased. From the single eligibility calculation in Table 2, only 27 percent of the households qualify as extreme vulnerable, 46 percent as extreme-and-mid vulnerable, and 63 percent as any vulnerable (extreme, mid, and vulnerable). Although expanding the humanitarian or government cutoffs would likely increase number of households referred, there are trade-offs in terms of referral success, referral failure, and failure to refer. For instance, an expansion of the humanitarian cutoffs beyond the extremely vulnerable group would increase the number of referrals but would also increase the probability of referring ineligible households, i.e., increasing the referral failure but increasing the absolute number of households referred. On the other hand, decreasing the humanitarian cutoff to capture only, for example, the extremely vulnerable groups would likely increase the probability of correctly referring eligible households, i.e., increasing the referral success, but decreasing the absolute number of those referred, and possibly failing to refer some eligible households. This trade-off reflects a concomitant political trade-off between maximizing the number of successful referrals (albeit at a lower success rate) and not mistakenly raising expectations (by referring fewer eligible households at a higher success rate but at a cost of not referring some eligible households). More so, expanding the eligibility coverage beyond the national bottom 18 percent to capture for example the bottom 25, or 30 percent would increase both the proportion and the actual number of cross eligible households, but obviously, increase the referral failure.

In addition, there is a question of how many households that are ineligible for the humanitarian assistance would, in fact, be eligible for the government support. The analysis show that among households that are not deem extremely vulnerable by the SEVAT, about 15 percent would be referred for government support under the program that includes only the bottom 18 percent nationally. The share decreases to 9 and 3 percent when the other two groups are included one by one and cumulatively. That means that a non-trivial number of households not considered extremely vulnerable by the humanitarian program would nonetheless be eligible for government assistance. From a policy perspective, this represents another trade-off. More total households would be successfully referred to the government programs if those *not* eligible for humanitarian assistance were also assessed; but the referral success rate among this group would be relatively low, possibly causing disappointment and frustration among the referral failures.

For the Legacy VA, about 20 percent of eligible households eligible for the humanitarian support under the extremely vulnerable group would be eligible for government support, and like that of the SEVAT, the proportion of cross eligible households decreases as the cutoff is expanded to include the less vulnerable groups. Similarly, 22 percent of those ineligible under the Legacy VA extreme vulnerable group would be eligible for the referral into the government’s SSN program. While the interpretation of the Legacy VA model is similar to that of the SEVAT, the observed difference is the share of cross-eligible households identified by the two models. Indeed, as shown in Table 3, the SEVAT tends to successfully refer more eligible households to government support compared to the Legacy VA, and the share of ineligible households referred is higher for the Legacy VA compared to the SEVAT. As discussed earlier, the discrepancies are caused by the closer similarity between the SEVAT model and the MoLSA model than the Legacy VA and MoLSA.

Table 3: Share of humanitarian beneficiary households that are referred to government support via the Full PMT model

Humanitarian caseloads		PMT cutoffs	GOI Social assistance simulated program coverage				
			Btm 15%	Btm 18%	Btm 25%	Btm 30%	Btm 35%
Eligible at different cutoffs	SEVAT	Extreme vulnerable (R3)	36	40	62	64	70
		Extreme-mid vulnerable (R2)	33	36	56	59	65
		Vulnerable (R1)	29	32	54	57	64
	Legacy VA	Extreme vulnerable	19	20	38	41	48
		Extreme-mid vulnerable	22	24	43	46	52
		Vulnerable	23	25	45	47	54
Ineligible at diff	SEVAT	Extreme vulnerable (R3)	14	15	32	35	42
		Extreme-mid vulnerable (R2)	8	9	26	29	36

	Legacy VA	Vulnerable (R1)	3	3	17	19	26
		Extreme vulnerable	21	22	42	45	51
		Extreme-mid vulnerable	16	18	36	39	46
		Vulnerable	15	16	33	37	44

Note: Values are in percentage cross-eligibility. The PMT cut-offs dictate the level of assistance a household receives: R1 (Vulnerable of 110,000 IQD) receives one transfer, R2 (Extreme-mid vulnerable or 92,000 IQD) receives two transfers and R3 (Extreme vulnerable or 70,000 IQD) receive three transfers. *Abbreviation Btm means Bottom.*

4.4 Pseudo PMT referrals and referral accuracy

The PPMT’s referral and performance accuracy is evaluated using two methods discussed in section 3.3. Referral rates applying the PPMT are presented in Table 4, while performance accuracy is presented in the Annex (Table A2 and A3) and a truncated version is shown in Table 5. The main result in Table 4 shows the percentage of households eligible under the extreme humanitarian cutoffs that are referred to government assistance by the PPMT under various expansion scenarios of the MoISA SSN program to the humanitarian caseload. Using the thresholds defined during the PPMTs development stage, the PPMT-SEVAT model would refer only 2 and 9 percent of the extremely vulnerable households to the government support at the 90 percent and 70 percent confidence level, respectively, when considering only those that are in the bottom 18 percent nationally (below the national poverty line). Even at a very low confidence level (50 percent CL), only about 19 percent of extremely vulnerable households of the humanitarian caseload would be referred to government assistance. For the same program size, the PPMT-Legacy VA model would refer 1 and 13 percent of the extremely vulnerable households to the government support at 90 and 70 percent confidence levels. At very low confidence level (50 percent CL), about 30 percent of the extremely vulnerable households would be referred. Part I of Table 5 a truncated version of the performance of the threshold approach, which set referral performance at varying levels of the MoLSA SSN program expansion size (only including those in bottom 15 to bottom 35 percent) and confidence levels (50 percent, 70 percent, and 90 percent) (See Table A2 in the annex for the complete version). The referral success of the threshold approach of the PPMT-SEVAT model is between 85 percent and 89 percent across the confidence levels, reflecting a very low level, between 12 to 15 percent, of inclusion errors referred to as “referral failure” in the paper. However, the proportion of eligible households it failed to refer, exclusion error, is very high (95 percent) if the referral is done at a high confidence level (90 percent CL). The failure to refer proportion is relatively lower at 58 percent for a low confidence level (50 percent CL). The results imply that the higher the confidence level, hence, the greater referral accuracy, smaller is the proportion of households that will be referred by the PPMTs.

Using the threshold PPMT method presents a trade-off; while almost all of those picked by the method at a very high confidence level would accurately be referred for the government support, it may exclude a significant number of cross-eligible households. The share of cross-eligible households referred by the method, however, would increase by decreasing the confidence level and/or extending the government program to less poorer households (increasing eligibility thresholds).

Moreover, as discussed, the PPMT can also be exploited by applying the more flexible ranking method, which would overcome such a trade-off. The high and significant rank correlations (0.7) between the PPMTs and full PMT (Table A1) suggest that the two formulas order the households similarly and it is appropriate to employ the “ranking” approach. We set the “pre-set” targeting rate same as the MoLSA simulated program size. For instance, for the program targeting households below the poverty line i.e., bottom 18 percent nationally, we set 18 percent as the “pre-set” targeting rate for the ranking method, i.e., the bottom 18 percent of the households in the PPMT score would be regarded as eligible.⁸ Under such scenario, both the PPMT-SEVAT and the PPMT-Legacy VA models would refer about 36 percent of the extremely vulnerable households to the government support. Part II of Table 5 shows that a high referral success (e.g., 77 percent in the PPMT-SEVAT model) and a low failure to refer (30 percent in the PPMT-SEVAT model) is achieved with the ranking method. That is, simply ranking referrals based on their score but not placing a maximum referral threshold means many more households will be referred and with relatively low referral failure.

Given the significant difference between the scope and hence the survey methodologies between the SWIFT on which the PPMT is designed and the CLCI’s verification field-test survey to which the PPMT is applied, the ranking method is more appropriate; a small reduction in successful referral rates compared to a much greater number of successful referrals and a slightly larger number of disappointed referrals is arguably preferable.

Table 4: Share of humanitarian beneficiary households (extremely vulnerable groups) that are referred for government support by the PPMT model

			GOI social assistance simulated program coverage					
	PPMT cases	Referral confidence level	Referral poverty line (log)	Btm 15%	Btm 18%	Btm 25%	Btm 30%	Btm 35%

⁸ Ideally, one should use the rate based on the targeting criteria for the government’s program that is specific to the group or region that the data represents. Therefore, the ideal rate for this field-experiment data would be the poverty rate among the IDPs and returnees in the Northern governorates for a MoLSA program targeting households below the poverty line. Unfortunately, we do not have such information.

PPMT – SEVAT	Threshold approach	90%	4.2	1	2	2	2	5
		80%	4.4	3	3	5	5	13
		70%	4.5	5	9	9	13	19
		60%	4.6	9	13	19	19	29
		50%	4.7	13	19	29	29	41
	Ranking approach			32	36	43	51	58
PPMT – Legacy VA	Threshold approach	90%	4.2	1	1	4	4	7
		80%	4.4	4	7	13	13	22
		70%	4.5	7	13	22	22	42
		60%	4.6	13	22	30	30	60
		50%	4.7	22	30	42	60	60
	Ranking approach			31	36	46	52	57

Note: Values are in percentage

Table 5: PPMT Performance Rates: at 18% National Cutoff, Extreme Vulnerable Only

	Part I: Threshold						Part II: Ranking	
	90% confident		70% confident		50% confident			
	SEVAT	Legacy	SEVAT	Legacy	SEVAT	Legacy	SEVAT	Legacy
Referral failure	15	21	12	29	15	50	23	25
Referral success	86	79	89	71	85	50	77	75
Failure to refer	95	95	81	55	58	27	30	15

4.5 Disaggregated result and unwillingness to be referred

The first issue addressed in the disaggregated analysis is the differences across various groups of interest. Table 6 shows the disaggregated percentage of the Field Test sample that are eligible for both MOLSA and humanitarian case support. The result shows how cross-modal eligibility rates of the full PMT differ across households with different socioeconomic characteristics: female-headed households, households with high disability and chronic illness, households with deficient assets, households with no working members. It also disaggregated households on their displacement status: host, displaced, and returnee households, and household location in different governorates.

The analysis finds that among households eligible for the humanitarian assistance, socioeconomic variables such as households at the lowest quantile of asset accumulation, households with no member has worked within the last 7 days, and households living in the rural areas are more likely to be eligible for the government support. About 56 percent of humanitarian beneficiaries at the lowest quantile would

be referred to the government program. Likewise, 51 percent of households where no member has worked and 41 percent of households living in rural areas would be referred. On other socioeconomic variables of interest, 39 percent of households with disabled heads, 39 percent of households who self-identified that they cannot afford basic needs, 38 percent of households whose heads' civil documentation is missing, and 27 percent of female-headed households would be also be eligible for the referral to the MoLSA program. The cross-eligibility model at its very restricted form – i.e., focusing on the extremely vulnerable households, is more likely to pick households that are disproportionately limited in livelihood sources, such as households with limited households' assets, which would have been valuable in times of hardship. Households where none of the members are employed or where the head is disabled also face significant challenges as they have limited sources of income and may depend fully on the support from the humanitarian agencies or the government for their survival.

On displacement status, eligible displaced and returnees are more likely to be referred to government support than the eligible host households. The table shows that 47 percent of displaced households and 39 percent of returnee households who are eligible for humanitarian assistance would be eligible for referral compared to 27 percent of host households. Most displaced households, especially those without documents, may face challenges in securing employment, while returnees also need a significant amount of support to rebuild their houses and restart their lives. Within the governorate, we found significant differences in the share of the cross-eligible households, with eligible households living in Ninawa (62 percent) and Anbar (24 percent) being more likely to be referred to the government support program than those living in Kirkuk (14 percent), Salahaldin (8 percent) and Diyala (3 percent).

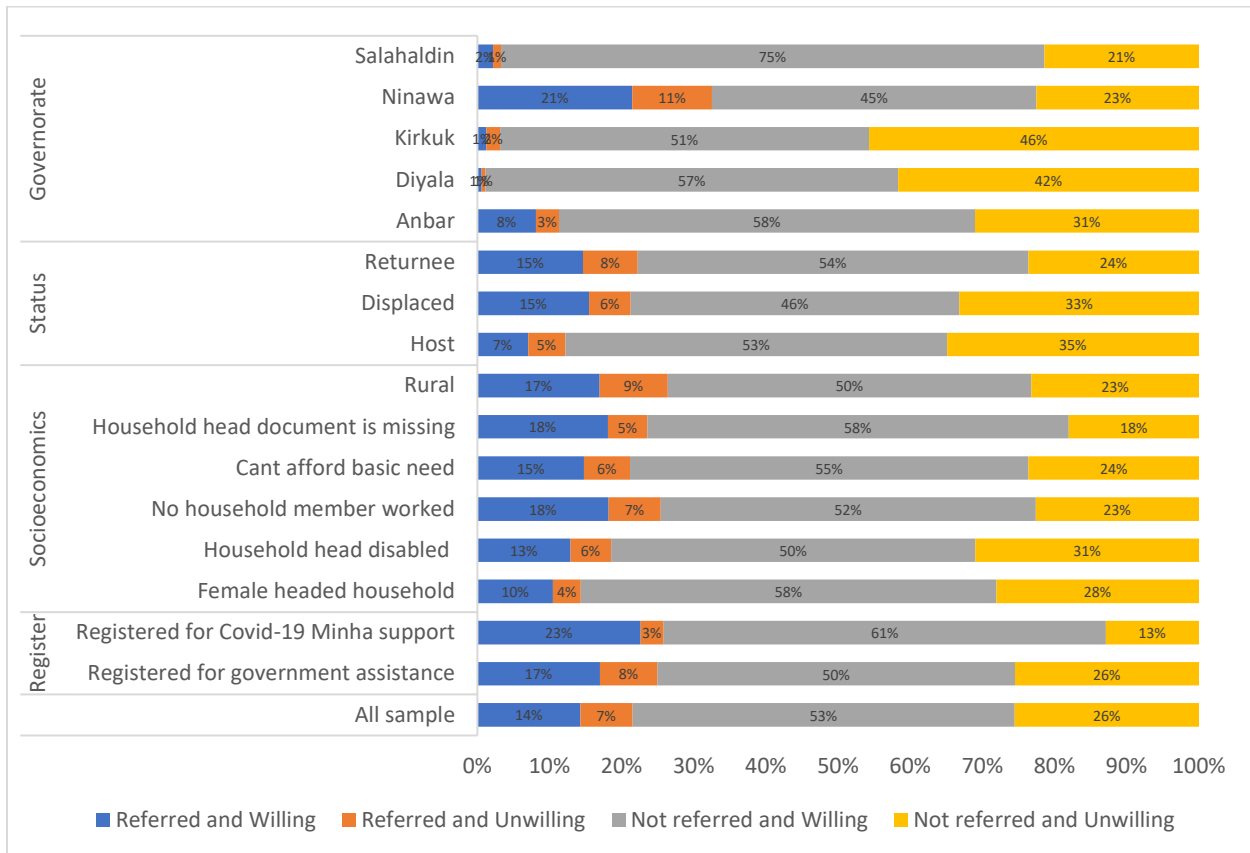
Table 6: Result of the disaggregated analysis

Variables	MoLSA (bottom 18%)	SEVAT (extreme vulnerable)	Cross eligible (Full PMT)
All sample	21%	27%	40%
Socioeconomics	Female-headed household	14%	27%
	Household head disabled	19%	30%
	No household member worked	25%	27%
	Can't afford basic need	21%	34%

	The household head document is missing	24%	26%	38%
	Asset lowest quantile	38%	33%	56%
Status	Rural household	26%	37%	41%
	Host	12%	23%	27%
	Displaced	21%	24%	47%
	Returnee	22%	28%	39%
Governorate	Anbar	11%	37%	24%
	Diyala	1%	40%	3%
	Kirkuk	3%	14%	14%
	Ninawa	33%	24%	62%
	Salahaldin	3%	28%	8%

Finally, the calculation shows that almost a third of eligible households may not be willing to be referred to the government support program due to fear, grievance, or other sociopolitical reasons. The share of unwilling households is relatively consistent (about 30 percent) across different groups – among the total sample, households eligible for government support using full-PMT, classified as extremely vulnerable or other vulnerable categories, as well as the humanitarian beneficiaries that are deemed eligible for referral using the full PMT or the PPMT. The crosstab for referral and unwillingness for all samples and some variables of interest is shown in Figure 2. The largest bar - grey color - represents the share of households that are willing but not referred by the full PMT. This is followed by the yellow bar which shows the share of households that are unwilling but not referred by the full PMT. The blue bar is the best match, showing the proportion of the households willing and referred to the government support. The smallest orange bar represents the share of households who are unwilling but are referred. This orange bar is of more significant, as it represents those who would be eligible for the referral but may likely decline. This group represents 7 percent of the total sample or about one-third of those eligible for referral.

Figure 2: Eligibility and willingness to be referred



A third of eligible households for humanitarian support opting out of government support is indeed high and may pose problems both in program planning as well as meeting government developmental goals. First, the unwillingness to be referred would likely reduce the odds of successful referrals. Second, while some mechanisms could be used to replace these unwilling groups for example using the higher eligibility threshold to include lesser poor households from the humanitarian caseload, this, however, may not be encouraged in the spirit of reconciliation and national building after many years of conflict. There is a need to understand the grievances of these groups and tackle them to find appropriate solution. Knowing their characteristics is the first step. As seen in Figure 2, Ninawa governorate is more likely to host households that are eligible but not willing to be referred (11 percent of the total sample of Ninawa), compared to other governorates, the percent is less than 3. They are more likely to be returnee households (8 percent) may also have applied for government assistance (8 percent) previously.

5. Conclusion

The need to expand the assistance and protection for conflict-affected populations beyond humanitarian aid cannot be overemphasized. The debate on how to expand government supports to IDPs has been ongoing for several years. Although certain frameworks are available in the literature, there is limited evidence of practical application of frameworks in a real-world setting. This paper adds to this ongoing debate and goes beyond framework development to a demonstrated application on this topic in Iraq.

This paper investigated a possible approach to bringing the humanitarian caseload into the government SP programs by exploiting data from a field test. As part of the CLC's recertification and enrollment process in the Northern conflict-affected governorates, a field survey asked the complete set of questions required to construct a full set of variables used in both the humanitarian and government cash transfer targeting models from the same households. It also collected information on perception and willingness to be referred to the government's program. Just because a household is likely eligible does not necessarily mean it is willing to be referred for assistance from the government. A combination of likely eligibility and willingness will ultimately determine how many potential MoLSA beneficiaries could come from the humanitarian database.

Analyzing the field-test data, this paper reconfirmed the findings from the desk review that a significant number of households that qualify for the humanitarian MPCA assistance are also eligible for the government's cash transfer program. Among households identified as extremely vulnerable by the Socio-Economic Vulnerability Assessment Tool (SEVAT) used by the MPCA since 2019, 40 percent of the beneficiaries would be eligible for the government's program when the targeting is limited to those below the national poverty line (a medium-small program). The referral rate would increase to 70 percent when the program expansion included everyone in bottom 35 percent nationally or within 1.36 times the poverty line (a large program). Under the same two expansion scenarios, 20 and 48 percent of the extremely vulnerable group identified by the old MPCA targeting tool, Legacy-VA, would be eligible for the referral. Intriguingly, a meaningful share of households that are deemed non-vulnerable and, hence, ineligible for any humanitarian assistance would, in fact, be eligible for government support - 3 and 26 percent among SEVAT non-eligible, and 16 and 44 percent among Legacy-VA non-eligible under the medium-small and large program expansion scenarios. These differences could be due to the fact that the two programs use different base data sets, and have slightly divergent focuses (vulnerability versus monetary poverty). Moreover, the data showed that a significant, one-third, share of humanitarian

beneficiaries that are eligible for the referral are unwilling to be referred to the government support program.

The PPMT models proposed during the desk review have high referral accuracy rates, low inclusion errors, but are also likely to leave out a number of eligible households (high exclusion error). The PPMT was devised using just the overlapping variables between the targeting models of the humanitarian and government support systems to overcome the need for collecting new data and rely on an already existing database. Using the eligibility thresholds presented in Phadera et al. (2022) as hard cutoffs, inclusion errors of both the PPMT models corresponding SEVAT and Legacy-VA would be (15 and 21 percent) well within the levels observed in practice; however, they would come at a cost of high exclusion errors (95 percent for both the models). When applying the more flexible ranking method, which is likely to overcome the disparities arising due to difference in type of data used, exclusion errors would be within the acceptable level of 30 and 15 percent for the PPMT corresponding to the SEVAT and Legacy-VA models. The referral rate among the extremely vulnerable households would be about 36 percent using both models.

The choice between electing to collect new data or to rely on the PPMT and use existing data comes with important trade-offs. The PPMT's ability to estimate referral on the already existing database would avoid the time and resources needed to collect new data. Particularly, the tool would be useful in the case of lack of budget, capacity (both common problems), or other circumstances such as insecurity. The PPMT models are estimations and therefore are not 100 percent accurate; hence, some eligible households will not be referred, and some ineligible households will be. While we have provided the confidence levels of the PPMT, the choice of PPMT depends on the level of risk that the government intends to take and the level of resources, both time and monetary, available to the government. Decreasing the confidence level would increase the number of people referred but increase the chances that some ineligible people could be referred, raising budgeting concerns. Increasing the confidence level would reduce the number of people referred, increase the referral success, but also increase the possibility that some eligible households would not be referred. Those not referred may become unhappy, and may develop an antagonistic attitude towards the government, which is not good in a country recovering from conflict. In this case, the adoption of grievance address systems such as phase-in approaches where households would be included in the program sequentially could be considered. Collecting new data and applying the full-PMT, on the other hand, has the advantage of identifying the referral eligibility with certainty. It can also elicit additional insights that, otherwise, would be missed and may prove crucial for planning the

possible transition. For instance, it would allow to assess the eligibility of the poor households that are considered non-vulnerable for the humanitarian assistance and thus, not included in their database. Moreover, perceived ISIS affiliation, fear of persecution, and other grievances may mean not all eligible households will be willing to be referred to the formal government social protection. The drawback, however, is that it comes at a great cost, as the door-to-door survey sweeps are very expensive. Of course, if funding permits, all vulnerable IDP households should be referred to government support. The approach which identifies all eligible households is to conduct a very large and costly new data collection effort, visiting all households. Which could be the preferred choice for policy makers depending on their capacity, budget, and appetite for the uncertainty of eligibility. However, in the absence of resources to conduct a new data collection (common in many places), the ranking approach of the PPMT model could serve as an acceptable substitute.

References

- Beegle, K., De Weerd, J., Friedman, J., & Gibson, J. (2012). Methods of household consumption measurement through surveys: Experimental results from Tanzania. *Journal of Development Economics*, 98(1), 3–18. <https://doi.org/10.1016/j.jdeveco.2011.11.001>
- Dutta, I., Foster, J., & Mishra, A. (2011). On measuring vulnerability to poverty. *Social Choice and Welfare*, 37(4), 743–761. <https://doi.org/10.1007/s00355-011-0570-1>
- Gentilini, U., Laughton, S., & Brien, C. O. (2018). Humanitarian Capital? Lessons on Better Connecting Humanitarian Assistance and Social Protection Ugo. In *Social Protection & Jobs* (No. 1802). <http://documents.worldbank.org/curated/en/946401542689917993/Humanitarian-Capital-Lessons-on-Better-Connecting-Humanitarian-Assistance-and-Social-Protection>
- International Organization for Migration (IOM). (2019). *Access to Durable Solutions among IDPs in Iraq. Experiences applying to compensation* (Issue April). [https://reliefweb.int/sites/reliefweb.int/files/resources/IOM Iraq Access to Durable Solutions Among IDPs in Iraq- Experiences Applying to Compensation.pdf](https://reliefweb.int/sites/reliefweb.int/files/resources/IOM%20Iraq%20Access%20to%20Durable%20Solutions%20Among%20IDPs%20in%20Iraq-Experiences%20Applying%20to%20Compensation.pdf)
- IOM. (2019). *Access to Durable Solutions Among IDPs in Iraq: Three Years in Displacement*. International Organization for Migration. <http://www.iomiraq.net/reports/iom-iraq-access-durable-solutions-three-years-displacement>
- Jovanovic, V., Douglas, L., Leape, V., Fox, G., Wai-Poi, M., Phadera, L., Sharma, D., & Westerman, O. (2021). *From Alignment to Integration: Lessons from Iraq on Linking MPCA and Social Protection Programming* (Issue September).
- Mitchell, A. (2018). *Harnessing social protection for forcibly displaced people- conceptual overview*. Social Protection across the Humanitarian-Development Nexus. <https://europa.eu/capacity4dev/file/81531/download?token=9V-x0ny2>
- O'Brien, C., Scott, Z., Smith, G., Barca, V., Kardan, A., Holmes, R., & Watson, C. (2018). Shock-Responsive Social Protection Systems Research Synthesis Report. In *Oxford Policy Management (OPM)*, (Issue January). <https://www.opml.co.uk/files/Publications/a0408-shock-responsive-social-protection-systems/srsp-synthesis-report.pdf?noredirect=1>
- Oxford Policy Management. (2015). *Shock-Responsive Social Protection Systems Research- Working*

paper 1: Conceptualising Shock-Responsive Social Protection (Issue October).

<https://www.opml.co.uk/files/Publications/a0408-shock-responsive-social-protection-systems/wp1-srsp-concept-note.pdf?noredirect=1>

Phadera, L., Sharma, D., Wai-Poi, M., Douglas, L., Jovanovic, V., Westerman, O., & Khan, S. A. (2022).

Bridging the Targeting Gap: Assessing Humanitarian Beneficiaries' Likely Eligibility for Social Protection in Iraq. *Policy Research Working Paper* (no. WPS 10093); June; Washington, D.C. : World Bank Group.

<http://documents.worldbank.org/curated/en/099255106172269568/IDU08944aa9c014e10467b0a196020a9f6950a59>

Pritchett, L., Suryahadi, A., & Sumarto, S. (2000). Quantifying Vulnerability to Poverty : A Proposed Measure, Applied to Indonesia. In *Policy Research Working Paper* (No. 2437; Issue September). www.worldbank.org/research/workingpapers.

Seyfert, K., Barca, V., Gentilini, U., Luthria, M., & Abbady, S. (2019). Unbundled: A framework for connecting safety nets and humanitarian assistance in refugee settings. In *Social Protection and Jobs Discussion Paper* (No. 1932; Issue 1935).

<http://documents.worldbank.org/curated/en/970701569569181651/Unbundled-A-Framework-for-Connecting-Safety-Nets-and-Humanitarian-Assistance-in-Refugee-Settings>

Sharma, D., & Poi, M. W. (2019). *Arrested Development: Conflict, Displacement, and Welfare in Iraq*.

<http://documents.worldbank.org/curated/en/914571554209012533/Arrested-Development-Conflict-Displacement-and-Welfare-in-Iraq>

UNHCR. (2019). Aligning Humanitarian Cash Assistance with National Social Safety Nets in Refugee Settings - Key Considerations and Learning. *UNHCR Report*. <https://www.unhcr.org/5cc011417>

World Bank. (2012). *Targeting: Poor and Vulnerable Households in Indonesia*.

<https://openknowledge.worldbank.org/handle/10986/26700> License: CC BY 3.0 IGO.

World Bank. (2017). *Forcibly Displaced: Toward a Development Approach Supporting Refugees, the Internally Displaced, and Their Hosts*. Washington, DC: World Bank. <https://doi.org/10.1596/978-1-4648-0938-5>

Annex

Table A1: Summary and correlation of the pmt scores

	Mean	Std. Dev.	Min	Max	Correlation (with MOLSA PMT)
MOLSA PMT	5.0	0.4	3.9	6.4	1
SEVAT	4.9	0.2	3.9	5.3	0.5***
LEGACY VA	19.6	9.1	0	52.0	-0.1***
PPMT -SEVAT	5.3	0.3	2.9	6.5	0.7***
PPMT -LegacyVA	4.9	0.3	2.8	6.3	0.7***

Note: The unit of PMT score of MPCA is Log10, the unit for legacy PMT score is the index between 0 and 50, and the unit of SSN is in **natural** log. The correlation was calculated using Spearman ranked. * significant at 10%, ** significant at 5%, and *** significant at 1%.

Figure A 1: Kernel density distribution of PMT scores.

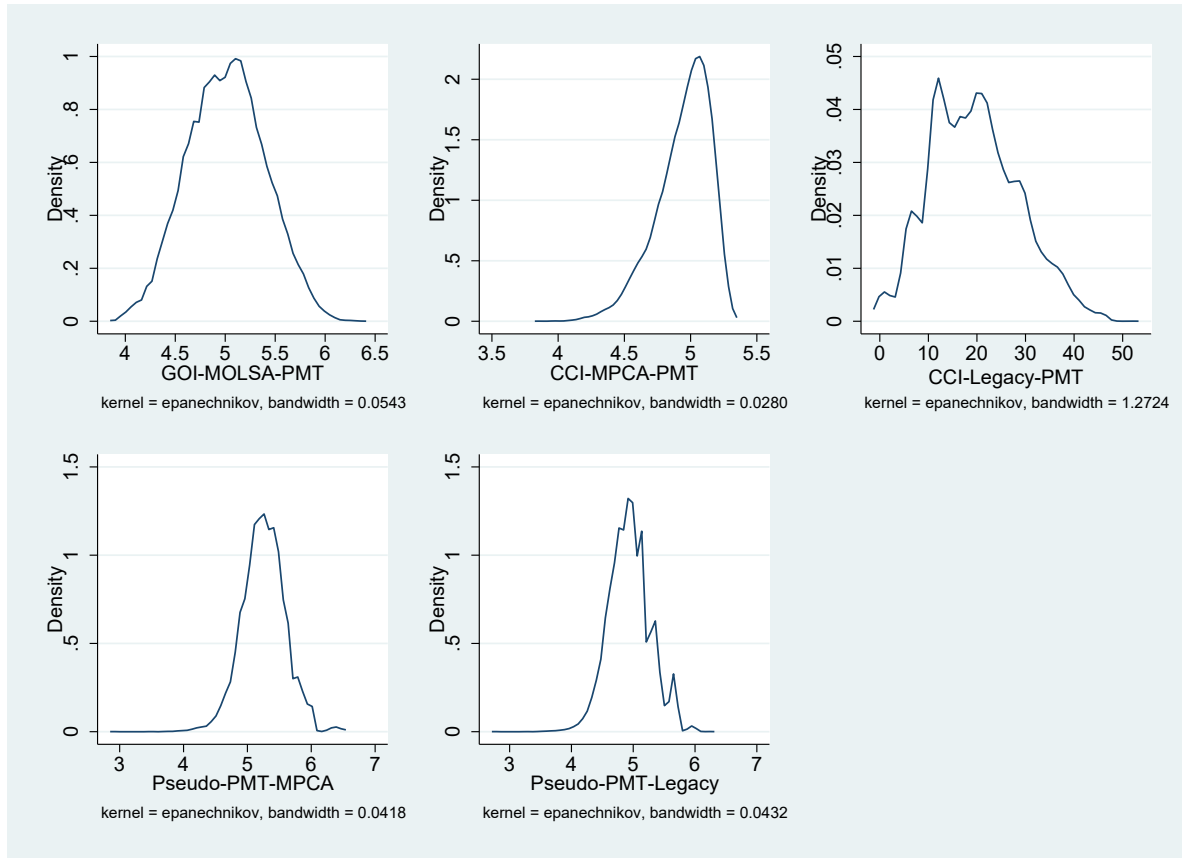


Table A2: Referral accuracy performance of the PPMT Threshold approach

A: PPMT referrals for SEVAT extreme vulnerable and MOLSA bottom 15%					
Referral confidence level =	90%	80%	70%	60%	50%
Referral poverty line (log)	4.2	4.4	4.5	4.6	4.7
Non-referral failure	35.0	34.0	32.8	30.9	28.2
Non-referral success	65.0	66.0	67.2	69.1	71.8
Referral failure	21.6	17.7	16.3	14.7	16.6
Referral success	78.4	82.3	83.8	85.3	83.4
Failure to refer	97.2	92.4	87.2	79.4	68.7
Failure to non-refer	0.4	0.9	1.4	2.0	3.4

B: PPMT referrals for SEVAT extreme vulnerable and MOLSA bottom 18%					
Referral confidence level =	90%	80%	70%	60%	50%
Referral poverty line (log)	4.3	4.4	4.6	4.6	4.8
Non-referral failure	38.5	38.0	35.0	32.3	28.7
Non-referral success	61.5	62.0	65.0	67.7	71.3
Referral failure	14.5	13.5	11.5	12.8	14.9
Referral success	85.5	86.5	88.5	87.2	85.1
Failure to refer	94.9	92.9	80.8	70.6	58.3
Failure to non-refer	0.6	0.7	1.6	2.8	4.8

C: PPMT referrals for SEVAT extreme vulnerable and MOLSA bottom 20%					
Referral confidence level =	90%	80%	70%	60%	50%
Referral poverty line (log)	4.3	4.5	4.6	4.8	4.9
Non-referral failure	44.9	43.4	41.6	35.2	29.6
Non-referral success	55.1	56.6	58.4	64.8	70.5
Referral failure	11.6	10.0	7.9	9.5	13.5
Referral success	88.4	90.0	92.1	90.5	86.5
Failure to refer	95.5	89.3	82.8	61.8	45.9
Failure to non-refer	0.5	1.0	1.3	3.4	7.2

D: PPMT referrals for SEVAT extreme vulnerable and MOLSA bottom 30%					
Referral confidence level =	90%	80%	70%	60%	50%
Referral poverty line (log)	4.3	4.5	4.7	4.8	4.9
Non-referral failure	63.2	62.1	58.9	56.3	51.7
Non-referral success	36.8	37.9	41.1	43.7	48.3
Referral failure	1.5	2.5	2.6	3.7	5.3
Referral success	98.6	97.5	97.5	96.3	94.7
Failure to refer	96.4	91.7	79.7	70.8	57.6
Failure to non-refer	0.1	0.4	1.0	2.0	4.3

E: PPMT referrals for SEVAT extreme vulnerable and MOLSA bottom 35%

Referral confidence level =	90%	80%	70%	60%	50%
Referral poverty line (log)	4.5	4.7	4.8	4.9	5.0
Non-referral failure	68.8	66.1	63.9	60.1	53.7
Non-referral success	31.2	33.9	36.1	39.9	46.3
Referral failure	0.0	1.0	2.1	3.8	5.3
Referral success	100.0	99.0	97.9	96.2	94.7
Failure to refer	92.3	81.3	73.1	60.8	45.0
Failure to non-refer	0.0	0.5	1.4	3.7	7.4

F: PPMT referrals for Legacy VA extreme vulnerable and MOLSA bottom 15%

Referral confidence level =	90%	80%	70%	60%	50%
Referral poverty line (log)	4.2	4.4	4.5	4.6	4.7
Non-referral failure	17.9	16.0	14.3	11.5	8.4
Non-referral success	82.2	84.0	85.7	88.5	91.6
Referral failure	24.6	16.3	23.3	32.9	45.5
Referral success	75.4	83.7	76.7	67.1	54.6
Failure to refer	94.9	83.0	72.0	53.9	35.1
Failure to non-refer	0.4	0.8	1.9	5.2	12.3

G: PPMT referrals for Legacy VA extreme vulnerable and MOLSA bottom 18%

Referral confidence level =	90%	80%	70%	60%	50%
Referral poverty line (log)	4.2	4.5	4.6	4.7	4.7
Non-referral failure	19.6	15.9	12.8	9.6	7.8
Non-referral success	80.4	84.1	87.2	90.4	92.2
Referral failure	21.1	19.0	28.6	41.9	50.1
Referral success	78.7	81.0	71.4	58.1	49.9
Failure to refer	95.2	73.0	55.1	36.8	26.8
Failure to non-refer	0.3	1.6	4.6	11.6	18.8

H: PPMT referrals for Legacy VA extreme vulnerable and MOLSA bottom 20%

Referral confidence level =	90%	80%	70%	60%	50%
Referral poverty line (log)	4.4	4.6	4.7	4.8	4.9
Non-referral failure	35.9	30.4	25.3	21.8	16.4
Non-referral success	64.1	69.6	74.7	78.2	83.6
Referral failure	1.6	8.4	16.1	22.9	31.1

Referral success	98.4	91.7	83.9	77.1	68.9
Failure to refer	90.3	69.4	51.6	39.9	25.1
Failure to non-refer	0.1	1.7	5.8	11.1	21.0

I: PPMT referrals for Legacy VA extreme vulnerable and MOLSA bottom 30%

Referral confidence level =	90%	80%	70%	60%	50%
Referral poverty line (log)	4.4	4.6	4.7	4.8	5.0
Non-referral failure	38.4	32.9	27.7	24.0	14.0
Non-referral success	61.7	67.1	72.3	76.0	86.0
Referral failure	1.6	6.9	14.0	20.3	41.3
Referral success	98.4	93.1	86.0	79.7	58.7
Failure to refer	90.9	70.7	53.2	41.5	14.0
Failure to non-refer	0.1	1.5	5.2	10.2	41.4

J: PPMT referrals for Legacy VA extreme vulnerable and MOLSA bottom 15%

Referral confidence level =	90%	80%	70%	60%	50%
Referral poverty line (log)	4.5	4.7	4.9	5.0	5.0
Non-referral failure	44.1	35.2	25.7	20.0	20.0
Non-referral success	55.9	64.8	74.3	80.0	80.0
Referral failure	2.4	8.2	21.4	33.4	33.4
Referral success	97.6	91.8	78.7	66.6	66.6
Failure to refer	86.1	57.5	31.4	16.9	16.9
Failure to non-refer	0.3	3.5	17.0	38.0	38.0

Table A3: Referral accuracy performance of the PPMT Ranking approach

A: PPMT referrals for SEVAT extreme vulnerable and MOLSA

Referral confidence level =	bottom15	bottom18	bottom20	bottom25	bottom30	bottom30
Referral poverty line (log)	4.93	4.95	4.96	5.05	5.07	5.15
Non-referral failure	17.2	18.8	23.1	40.5	39.8	45.7
Non-referral success	82.8	81.2	76.9	59.5	60.3	54.3
Referral failure	25.4	23.0	17.1	10.2	13.0	11.3
Referral success	74.6	77.0	82.9	89.8	87.0	88.7
Failure to refer	32.9	30.4	31.1	36.6	30.2	27.5
Failure to non-refer	12.6	13.6	12.1	11.8	18.5	22.0

B: PPMT referrals for Legacy VA extreme vulnerable and MOLSA

Referral confidence level =	bottom15	bottom18	bottom20	bottom25	bottom30	bottom30
-----------------------------	----------	----------	----------	----------	----------	----------

<u>Referral poverty line (log)</u>	4.61	4.63	4.68	4.72	4.76	4.82
Non-referral failure	18.3	20.2	24.9	39.9	36.6	45.2
Non-referral success	81.7	79.8	75.1	60.1	63.4	54.8
Referral failure	26.8	25.1	21.3	12.1	11.1	10.2
Referral success	73.2	74.9	78.7	87.9	88.9	89.8
Failure to refer	35.2	32.8	33.1	34.5	27.2	27.9
Failure to non-refer	13.1	14.8	15.4	14.7	16.2	19.5

Ranking method: Humanitarian PMT legacy