Hit and Miss:

An assessment of targeting effectiveness in social protection *with additional analysis*

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DEVELOPMENT PATHWAYS

Preface

This is a re-publication of a paper published in 2019 aimed at examining the relative effectiveness of different approaches to targeting. Using national household surveys, we examined 38 social protection schemes across 23 low and middle-income countries in the original publication. This re-publication includes additional analysis of four schemes across Bangladesh, Colombia and Sri Lanka which utilise a form of poverty-targeting. This has enabled us to strengthen the evidence presented in this paper. However, it has not changed any of the main findings discussed in the original conclusion of the paper.

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We hope that the paper will enable those working in social protection to reflect on the evidence we present on targeting effectiveness and commit to approaches that achieve the objective of leaving no-one behind. These approaches will require higher levels of investment, but the results will be worth it.

Stephen Kidd and Diloá Athias

Executive summary

Introduction

If countries and international agencies are truly committed to 'leaving no-one behind,' social protection schemes must be able to accurately identify their target populations. Therefore, the mechanisms chosen to target the intended recipients of social protection schemes need to be effective (or, some would say, effective enough). Yet, debates on the most effective means of targeting can generate strong emotions, with committed advocates on different sides of the argument. While some are true-believers in poverty targeting, others argue that a universal approach is the most effective. Nonetheless, it is essential that debates on the relative merits of different approaches to targeting are underpinned by evidence.

Therefore, the aim of the research outlined in this paper was to test the relative effectiveness of different approaches to targeting. Using national household survey datasets, we examined the targeting effectiveness of 42 social protection schemes across 25 low- and middle-income countries. Four of the schemes examined employed a universal approach while the others used some form of income-test: means testing, proxy means testing, community-based targeting, self-targeting and benefit testing.

The specific questions that the research sought to answer were:

- How effective are different types of targeting mechanism in reaching their intended recipients?
- How effective are different types of targeting mechanism in reaching those living in extreme poverty?

The analysis assessed schemes against their effectiveness in reaching their intended category of the population. So, for example, if a scheme was targeted at households with children living in poverty, its accuracy was assessed only against households with children (in other words, the intended category); or, if a scheme was an old age pension for people aged 65 years and above, it was tested against the intended category of older people aged 65 years and above.

The effectiveness of poverty targeting

The research examined the effectiveness of poverty targeting by assessing programmes or registries targeted at the poorest 25 per cent or less of their intended category. When tested against their effectiveness in reaching their intended recipients, the errors were high across all programmes and registries errors. Brazil's *Bolsa Família* scheme – which uses a simple means-test – was the most effective, yet still excluded 44 per cent of its

intended recipients. The worst performing programme was Rwanda's *Vision 2020 Umurenge* Programme (VUP) which employed community-based targeting: its exclusion error was 97 per cent. It was closely followed by Guatemala's *Mi Bono Seguro* scheme, which uses a proxy means-test and had an error of 96 per cent among intended recipients. In fact, out of 25 programmes or registries with coverage under 25 per cent, 12 had exclusion errors above 70 per cent and 5 had errors above 90 per cent.

Poverty-targeted schemes were also not particularly effective in reaching the poorest 20 per cent of their intended category. Only one programme – the Philippines' *Pantawid* programme – reached over half of the poorest 20 per cent of its intended category (households with children). Poverty-targeted programmes were consistently found to be excluding over half of the poorest quintile of their intended category. Uzbekistan's Low-Income Allowance and Rwanda's VUP public works programme were the worst performing with errors of 98 per cent. For small programmes with low coverage, some of the exclusion was the result of undercoverage as well as poor-quality targeting.

Overall, the results demonstrate a mass failure of poverty targeting across low- and middle-income countries. In programme after programme, the majority of both the intended recipients and the poorest members of society were excluded from social protection.

Relationship between the coverage of schemes and targeting effectiveness

Of course, as discussed above, not all social protection schemes are targeted at the poorest members of society. Some have high coverage while others offer universal access. The research, therefore, also examined whether higher coverage schemes – including those employing a universal approach – were more effective than poverty-targeted programmes in reaching both their intended recipients and those living in extreme poverty (in other words, the poorest 20 per cent of the intended category).

The research found, unsurprisingly, a strong relationship between higher coverage and lower exclusion of intended recipients. All four universal schemes performed well, with exclusion errors below 10 per cent. In fact, Georgia's universal Old Age Pension and Mongolia's universal Child Money scheme had errors below 2 per cent, both highly effective performances.

South Africa's social grant programmes offer relatively high coverage – though not fully universal – reaching over 70 per cent of their intended categories (children and older people). In effect, rather than targeting the poorest members of society, the schemes attempt to exclude those who are better-off, a form of affluence testing using a simple means-test. While they did not perform as well as universal schemes, their exclusion errors were much lower than programmes targeted at the poorest members of society: the

Old Age Grant's exclusion error was 8 per cent while it was 13 per cent for the Child Support Grant.

As indicated above, poverty-targeted schemes had the highest exclusion errors. Nonetheless, within poverty-targeted schemes, there is a similar correlation between higher coverage and lower errors. As a result, those with the lowest coverage – such as Ghana's LEAP programme, Uzbekistan's Low-Income Allowance and the VUP Public Works programme in Rwanda – tend to have very high exclusion of their intended recipients. As coverage expands, errors among poverty-targeted schemes reduce, although they remain high.

The research also compared the effectiveness of all types of targeting mechanism in reaching the poorest 20 per cent of the population within their intended categories. As with exclusion errors, the higher a scheme's coverage, the greater its effectiveness in reaching the poorest members of society. Universal and high coverage schemes perform particularly well, with exclusion below 10 per cent (in other words, over 90 per cent of the poorest 20 per cent were reached). In fact, three schemes – Georgia's Old Age Pension and South Africa's Old Age and Child Support Grants – have no measurable error, while Mongolia's universal Child Money scheme reached 99 per cent of the poorest 20 per cent of children. In contrast, as noted above, poverty-targeted schemes – which, ironically, aim to reach those living in extreme poverty – are much less effective than universal schemes with almost all excluding over half of the poorest 20 per cent of their target populations.

Results for specific targeting mechanisms and individual schemes

The paper also presents the results for each targeting mechanism and approach. These are summarised below.

- **Universal schemes** had the lowest errors and were the most effective in reaching both their intended recipients and the poorest 20 per cent within their intended categories.
- Despite claims that **means testing** is challenging to undertake in low- and middle-income countries, some means-tests performed well when compared to other income testing mechanisms. As indicated above, the simple means-test used in Brazil's *Bolsa Família* programme was the best performing poverty-targeted scheme although, to a large extent, this is likely due to its use of quotas in each municipality. South Africa's simple means-test was also relatively effective, although this is probably the result of its attempt to exclude the more affluent rather than targeting those living in extreme poverty.
- The results from schemes using **proxy means testing** varied greatly but contradict the claim by the World Bank that the proxy means-test 'can accurately and cost effectively target the chronic poor.' In line with the overall results, there was a

strong correlation between coverage and targeting effectiveness. So, some schemes with low coverage – such as Ghana's LEAP programme and Guatemala's *Mi Bono Seguro* scheme – had exclusion errors above 90 per cent. When coverage is taken into account, the most effective scheme was Peru's *Juntos* programme with an exclusion error of 46 per cent. India's Below Poverty Line uses a simple proxy means-test and was particularly ineffective, although much of this may be explained by corruption. The effectiveness of Kenya's Hunger Safety Net Programme (HSNP) – which performed little better than random selection – indicates that combining community-based targeting with proxy means testing is unlikely to enhance targeting effectiveness. A key challenge with proxy means testing is that it has very high design errors while further errors are incorporated during implementation. Proxy means testing forms the basis of many of the Social Registries currently being developed and implemented in low- and middle-income countries. However, in our research, all Social Registries using PMTs were failing badly.

- Few countries use **community-based targeting** at a national scale although it has been adopted by many small-scale donor-driven schemes in Africa. We examined three countries using community-based targeting and the results were variable. Vietnam's Poor List stands out as a relatively effective registry. It attempts to identify the poorest households in Vietnam and the exclusion error among the poorest 10.6 per cent of households identified as 'poor' was 49 per cent, making it one of the best performing schemes in our research. However, Ethiopia's Productive Safety Net Programme (PSNP) excluded 81 per cent of its intended recipients while Rwanda's VUP scheme excluded 95 per cent. While advocates of community-based targeting argue that 'communities know best' when selecting recipients of social protection schemes, the evidence suggests that this is an assumption based on a rather naïve view of communities as harmonious entities.
- The research only examined one scheme using **self-targeting**: India's Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) scheme, a workfare programme. Self-targeting in workfare schemes is based on the theory that, if a low wage is offered, only the poorest members of society will want to access the scheme. Our research indicated that, while MGNREGA reached 28.6 per cent of households in rural India in 2012, among the poorest 20 per cent, 61 per cent were excluded. Some of the errors are likely to be the result of the poor-quality implementation of the scheme in some areas of India.
- Two old age social pensions which used **benefit testing** were examined. A benefit-test means that only those not accessing another state pension are eligible. In theory, therefore, benefit testing should offer universal coverage through a combination of pension schemes (usually either funded from general taxation or

social insurance). However, both Mexico's *Programa 65 y Más* and Vietnam's social pension for those aged 80 years and above had relatively large exclusion errors: 40 and 48 per cent respectively. Based on this evidence, it would appear that, if countries wish to guarantee income security to all their citizens on reaching old age, a universal social pension is likely to be more effective than a benefit-tested option.

The poor: a fictional construct

There are many reasons for the limited effectiveness of poverty targeting and, often, they are particular to the specific scheme and the local design of the mechanism. However, a key cause of ineffective poverty targeting underpins all mechanisms everywhere: the belief that there is a fixed group of the population called 'the poor.' In reality, this is a fictional construct and, therefore, not a good basis for determining social policy, including who should be targeted by social protection schemes.

While it is common to refer to 'the poor' and 'non-poor,' in reality most people in low- and middle-income countries are living in poverty, with per capita consumption below US$5.00 or US$10.00 in purchasing power parity terms. Furthermore, incomes are highly volatile as the result of households experiencing risks and challenges or responding to opportunities. The paper shows how a household's ranking in the wealth distribution can change dramatically over periods as short as one or two years.

The implications of high levels of poverty and dynamic incomes are twofold: the vast majority of people living in low- and middle-income countries would benefit from access to social protection; and, targeting a fixed group called 'the poor' is not possible since those at the bottom of the wealth distribution constantly change. Both call into question the logic of poverty targeting.

Conclusion

The evidence produced by the research shows that universal and affluence-tested schemes are much more effective than poverty-targeted programmes in reaching both their intended recipients and those living in poverty. While this is an unsurprising finding, the scale of the errors with poverty targeted schemes is, perhaps, more unexpected. There is no evidence at all that poverty targeting in low- and middle-income countries can be undertaken with any degree of accuracy.

The results are further proof of the old adage that programmes for the poor are poor quality programmes. The belief among some advocates of poverty targeting that technology will bring about improvements is not borne out by the evidence: even in relatively advanced Latin America contexts with 'cutting-edge' Social Registries, the errors are high. Significant improvements are unlikely to happen with more technology.

If governments and international agencies are really committed to 'leaving no-one behind' and ensuring that the right to social security is fully realised, the evidence from our research demonstrates that it will be necessary to support universal social protection schemes within the context of inclusive, lifecycle social protection systems. Of course, universal programmes will require a higher level of investment than those using poverty targeting but the simple truth is that quality costs.

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Acronyms

4P	*Pantawid Pamilyang Pilipino Program* (The Philippines)
AF	*Asignaciones Familiares* (Uruguay)
APIS	Annual Poverty Indicators Survey (Philippines)
BDH	*Bono de Desarrollo Humano* (Ecuador)
BF	*Bolsa Família* (Brazil)
BISP	Benazir Income Support Programme (Pakistan)
BJP	*Bono Juancito Pinto* (Bolivia)
BPL	Below Poverty Line (India)
BRL	Brazilian Real
CA	Childcare Allowance (Uzbekistan)
CCT	Conditional Cash Transfer
CMP	Child Money Programme (Mongolia)
CSG	Child Support Grant (South Africa)
DFID	Department for International Development
DS	Direct Support
ECH	*Encuesta Continua de Hogares* (Uruguay)
ECV	*Encuesta Nacional de Calidad de Vida* (Colombia)
EICV	*Enquête Intégrale sur les Conditions de Vie des ménages* (Rwanda)
ENAHO	*Encuesta Nacional de Hogares sobre Condiciones de Vida y Probeza* (Peru)
ENAP	*Escola Nacional de Administração Pública* (Brazil)
ENCOVI	*Encuesta Nacional de Condiciones de Vida* (Guatemala)
ENCV	*Encuesta de Condiciones de Vida* (Ecuador)
ENIGH	*Encuesta Nacional de Ingresos y Gastos de los Hogares* (Mexico)
ESS	European Social Survey
FA	Family Allowance
FAP	*Familias en Acción Programa* (Colombia)
FB	Family Benefits
GDP	Gross Domestic Product
GDPR	General Data Protection Regulation
GHS	General Household Survey (South Africa)
GLSS7	Ghana Living Standards Survey
HIES	Household Income and Expenditure Survey (Sri Lanka)
HIES	Household Integrated Economic Survey (Pakistan)
HILCS	Households Integrated Living Conditions Survey (Armenia)
HSES	Household Socio-Economic Survey (Mongolia)
HSNP	Hunger Safety Net Programme (Kenya)
IDA	International Development Association
IHDS	India Human Development Survey
IMF	International Monetary Fund
KIHBS	Kenya Integrated Household Budget Survey
KPS	*Kartu Perlindungan Sosial* (Social Protection Card – Indonesia)
L2CU	Listening to the Citizens of Uzbekistan
LEAP	Livelihood Empowerment Against Poverty (Ghana)
LIA	Low-Income Allowance (Uzbekistan)

LSMS	Living Standards Measurement Study (Albania)
MBS	*Mi Bono Seguro* (Guatemala)
MGNREGA	Mahatma Gandhi National Rural Employment Guarantee Act (India)
NE	*Ndihme Ekonomike* (Albania)
NRGEA	National Rural Employment Gurantee Act (India)
OAG	Old Age Grant
OAP	Old Age Pension
PKH	*Program Keluarga Harapan* (Indonesia)
PMT	Proxy Means-Test
PNAD	*Pesquisa Nacional por Amostra de Domicílio* (Brazil)
PPP	Purchasing Power Parity
PSNP	Productive Safety Net Programme (Ethiopia)
PSSN	Productive Social Safety Net (Tanzania)
PW	Public Works
RD	*Renta Dignidad* (Bolivia)
SASSA	South African Social Security Agency
SCA	Senior Citizens' Allowance (Sri Lanka)
SDR	Special Drawing Rights
SUSENAS	Survey *Sosial Ekonomi Nasional* (Indonesia)
TSA	Targeted Social Allowance
UK	United Kingdom
UNICEF	United Nations International Children's Emergency Fund
USA	United States of America
VHLSS	Vietnam Household Living Standards Survey
VUP	*Vision 2020 Umurenge* Programme
WMS	Welfare Monitoring Survey (Georgia)

1 Introduction

Accurate targeting is the Holy Grail of social protection. A range of governments and international organisations have invested vast sums in trying to develop effective mechanisms for identifying the poorest members of society. Each targeting methodology has its advocates and it is not unusual for the true-believers in a particular mechanism to make strong claims about its effectiveness. Take for example the statement in a World Bank technical note that the proxy means-test 'can accurately and cost effectively target the chronic poor.'[1] Others believe in the virtues of community-based targeting on the grounds that 'the community knows best' while many argue in favour of universal selection, reasoning that it is important to guarantee the right of everyone to social security.

Debates on targeting frequently generate powerful emotions. Indeed, some institutions feel so strongly about it that they have even used threats to force countries to change their approach. For example, in 2017, the World Bank, International Monetary Fund and Asian Development Bank pressured the Government of Mongolia into using a proxy means-test instead of universal selection in its Child Money scheme by threatening to withhold much-needed loans.[2]

Countries invest in social protection for a range of reasons, such as promoting economic growth, strengthening human development or ensuring dignity for all citizens. But, at its heart, social protection aims to ensure that all members of society can access a minimum income. To achieve this aim, social protection systems need to ensure that they can effectively reach the poorest members of society so that no-one is left behind. Indeed, the rationale for investing in a child benefit, for example, would be shaken to its core if the poorest children were excluded.

However, it is essential that debates on the relative merits of different approaches to targeting are based on evidence. Too often, policymakers have been persuaded to adopt a particular targeting mechanism, often investing tens of millions of dollars, only to find that it does not work. Or, perhaps even worse, they have been told that it is working when, in reality, the majority of the intended recipients have been excluded.

The aim of this paper is to set out the evidence on the effectiveness of different approaches to targeting. Specifically, it aims to answer two questions:

[1] Leite (2014). See also Del Ninno and Mills (2015) who make the same claim.

[2] Kidd (2018a; 2018b).

- How effective are different types of targeting mechanism in reaching their intended recipients; and,
- How effective are different types of targeting mechanism in reaching those living in extreme poverty?

We have tried to answer these questions by analysing 25 national household datasets across low- and middle-income countries in Africa, Asia and Latin America, with occasional references to other publications. By using household survey datasets that included information on whether individuals or households were in receipt of a transfer, we were able to examine the actual targeting effectiveness of social protection schemes. Therefore, the paper takes a different approach to that of Kidd and Wylde (2011), Kidd et al (2017) and Brown et al (2018) which examined the theoretical design errors of the proxy means-test but not their actual performance.

The research does not examine a range of other parameters that could be used to assess targeting methodologies, such as: the level of investment (universal schemes are, generally, more expensive than poverty-targeted programmes);[3] administrative costs (poverty targeting is more complex than universal selection so, if implemented seriously, the administrative costs are higher); human rights considerations and principles, including equity, non-discrimination, dignity and transparency (universal schemes are much more likely to be aligned to a human rights approach than those using poverty targeting); social costs (poverty-targeted programmes tend to be more socially divisive than universal schemes and are more likely to stigmatise recipients); incentive costs (poverty-targeted programmes are more likely than universal schemes to discourage people from working); and their popularity (universal schemes tend to be much more popular than poverty-targeted programmes, since the latter exclude the majority of the population). Further information – and a range of views – on these topics can be found in Sen (1995), Coady et al (2004), Mkandawire (2005), Fischer (2010, 2012, 2013, 2018), Sepúlveda and Nyst, (2012), Kidd and Bailey-Athias (2016), Kidd (2017c), Kidd, Gelders and Bailey-Athias (2017) and Devereux et al (2017).

The research findings are clear and not unexpected. We find that accurate and effective poverty targeting is impossible to achieve and, indeed, errors across all poverty-targeted programmes are high. We even find examples of poverty targeting where almost all intended recipients were excluded. In fact, even in schemes investing significantly in technologies to improve targeting – and which are lauded by advocates of poverty

[3] It is often assumed that a low level of investment in social protection is positive. However, low levels of investment – which imply lower coverage and lower transfer values – reduce the effectiveness of schemes while the benefits, such as impacts on economic growth, are also reduced. Indeed, the view that a low level of investment in social protection is positive is an ideological position, reflecting a belief in low taxes and a small state.

targeting – the results are very poor. We also find that higher coverage of social protection schemes results in lower errors and greater inclusion of the poorest members of society, with universal schemes, as expected, the most effective. To a large extent, this is common sense, but it is surprising how often this simple fact is not recognised: at least we now have the evidence.

The paper begins, in Section 2, by providing an overview of the meaning of targeting within social protection and the different types of targeting mechanisms that were analysed during the research. In Section 3, we describe our research methodology and Section 4 presents the results at a global level. Section 5 provides more details on the results for each programme assessed while Section 6 examines income dynamics, one of the key causes of targeting inaccuracy. Section 7 concludes the paper.

Box 1: A note on nomenclature

Throughout the paper, we repeatedly used two terms when analysing targeting effectiveness: intended category and intended recipients. The meaning used in this paper for these terms is set out below:

- The ***intended category*** refers to those belonging to the category of the population that incorporates those who are eligible for a particular scheme. So, the intended category of an old age pension for those aged 65 years and above living in poverty is people aged 65 years and above; and, the intended category for a programme targeted at 'poor households' is all households.
- The ***intended recipients*** refers to those who are eligible for a scheme. In poverty-targeted programmes, we assume that the coverage of the scheme among the intended category indicates the intended recipients. So, if a poverty-targeted household benefit reaches 10 per cent of households, the intended recipients are assumed to be the poorest 10 per cent of households. And, for a universal child benefit, the intended recipients are all children.

2 An overview of targeting mechanisms

While 'targeting' is often conceptualised as a simple process of identifying 'the poor,' in reality, in the context of a national social protection system, it should be understood as comprising four stages, beginning with policy decisions on the aim of a scheme and concluding with the registration of recipients. These stages are summarised in Figure 1 and discussed in more detail below.

Figure 1: The four stages of the targeting process

In ***Stage 1***, governments decide which social issue they wish to tackle through social protection. It may be that offering income security and dignity to all citizens once they reach old age is a policy priority, which would mean that the focus would be on establishing an old age pension.[4] Alternatively, governments may want to give every citizen a great start in life, which may mean developing a child benefit.

Once the social issue to be addressed has been identified, in ***Stage 2*** governments decide whether to dedicate sufficient resources to address the issue effectively – by ensuring that everyone in the intended category can be included in the programme (in other words, a universal programme) – or reduce costs by selecting a smaller number of potential recipients. There are two basic options for reducing coverage: a government could either narrow the category selected – such as by restricting an old age pension to a higher age group – or target the programme at those living in poverty (or both).

In ***Stage 3*** of the targeting process, governments design the actual mechanism for identifying recipients. If the scheme has maintained universal coverage – even with a

[4] In this paper, when we use 'citizens' we mean all those legally in a country.

narrowed category – this is a simple process, since everyone within the category is eligible to receive the scheme. However, if governments have chosen to target 'the poor,' the design is more complex since a mechanism for identifying the poorest members of the intended category has to be developed.[5]

Stage 4 is the actual process of implementing the selection mechanism through the registration and enrolment of applicants.

The analysis in this report focuses on Stages 2 to 4, following the policy decision in Stage 1. A key distinction occurs in Stage 2 when a government decides either to opt for universal coverage of the population affected by the policy choice made in Stage 1 – in other words, the intended category – or restrict coverage through some form of income or wealth test.[6] Therefore, the analysis in this report distinguishes between a ***universal approach*** to selecting recipients of a scheme and targeting on the basis of an income or wealth test, in other words, ***poverty targeting***. Often lifecycle social protection systems are said to employ 'categorical targeting' but, as we explain in Box 2, we believe that this is a misunderstanding.

During Stage 3 of the selection process, if poverty targeting is used, a targeting mechanism has to be designed. There is a range of poverty targeting mechanisms used across low- and middle-income countries. The most common mechanisms are discussed in Sections 2.2 and 5.2 of the report. Stage 4, as indicated above, is when the targeting mechanism or universal approach is implemented on the ground.

Errors in targeting can happen during both Stages 3 and 4 of the selection process. Errors introduced in Stage 3 are often referred to as ***design errors***: in other words, they are the targeting errors resulting from the design of the programme itself. As will be seen in Section 5.2.2, proxy means testing is an example of a targeting mechanism incorporating high design errors. ***Implementation errors*** are those that occur during the registration process.

The following sections provide a brief description of the different types of targeting mechanism examined in this report.

[5] Although this paper does not examine disability benefits – see Kidd et al (2019b) for further information on this – it should be recognised that identifying people with disabilities also requires a disability assessment process to be developed, which can be complex.

[6] As indicated in the main text, governments can restrict coverage by other means, for example by reducing the size of the category identified by the policy choice through, for example, changing age eligibility in a lifecycle scheme, such as an old age pension or child benefit. A number of countries have introduced old age pensions with a high age of eligibility which, over time, is reduced (such as Nepal and Vietnam). However, for the purposes of the analysis in this paper, as long as everyone in the age group selected is eligible for the programme, we consider the scheme to be using a universal approach.

Box 2: Categorical targeting or lifecycle schemes?

Often, the term 'categorical targeting' is used to refer to a type of targeting mechanism. Those using the term regard categories of the population – such as children, people with disabilities or older people – as a 'target.' They argue that these categories can be used as a means of 'targeting the poor' when there is some correlation between the category of the population and poverty (e.g. Coady et al 2004; Devereux et al 2017). Some would argue, however, that what is referred to as categorical targeting is, in reality, governments making the policy choice – in Stage 1 of the process – to address particular contingencies or risks across the lifecycle (Kidd 2013). As a result, governments introduce ***lifecycle social protection schemes*** such as child benefits, disability benefits, unemployment benefits and old age pensions (and often they are delivered using a combination of social insurance and tax-financed schemes). When such schemes are offered on a universal basis, they are available to all citizens at the point of the lifecycle when they require them. Lifecycle social protection systems are characteristic of high-income countries and increasing numbers of low- and middle-income countries.

However, when a lifecycle scheme is offered only to those living in poverty – such as India's Old Age Pension – it should be regarded as employing poverty targeting.

2.1 Universal approaches to identifying recipients

A universal approach to identifying recipients of social protection schemes is very simple since everyone within the intended category of the population is eligible for the scheme. So, for example, if a tax-financed social pension is offered to everyone above a particular age, applicants usually only need to provide evidence of age; similarly, in a universal child benefit, applicants only need to demonstrate that their children exist – often by presenting a birth certificate – and are under the age of eligibility. A universal basic income would offer a scheme to each individual, although such schemes are rare: probably, Iran's unconditional cash transfer – which replaced its oil and bread subsidies in 2010 – is probably the national social security scheme most closely resembling a universal basic income.[7] A universal approach is also common in education and health programmes: for example, universal basic education offers all children access to schools; and, a free tax-financed health system, such as the United Kingdom's National Health Service, enables anyone who is ill to access health services.

Universal schemes may incorporate some limited restrictions. Most often these are linked to residence with applicants needing to have been resident in the country for a minimum number of years before they can access a scheme. For example, New Zealand requires ten

[7] Guillaume et al (2011). *Note*: The basic income scheme offers each person in a household an equal income. However, it is given as only one payment per household and each household can receive transfers up to a maximum of six household members.

years of residence – including five from 50 years of age – before people can access its social pension, known as the New Zealand Superannuation scheme.[8]

2.2 Poverty targeting

As indicated above, the analysis has examined five types of poverty targeting mechanism. Three have the clear aim of identifying the poorest members of society: means testing, proxy means testing and community-based targeting. Self-targeting is a mechanism that aims to disincentivise those on higher incomes from participating in a scheme. Benefit-testing, while not strictly poverty-targeted, nonetheless employs a simple form of income-test. Each is discussed in turn.

2.2.1 Means testing

Means testing involves assessing the income or wealth of applicants of poverty-targeted schemes. Usually, an income or wealth eligibility line is set and all those with incomes or wealth below the line are deemed to be eligible. Assessments can be undertaken of individuals, families or households, depending on the type of scheme.

Means testing is very common in high income countries where the vast majority of the labour force is in the formal economy and it is relatively easy to verify incomes. However, it is often regarded as a costly mechanism to implement in low- and middle-income countries. For example, Devereux et al (2017) argue that it is 'the most data-demanding (and most expensive) targeting mechanism.'[9] In reality, this is not always the case since, in some middle-income countries, the means-test is based on an applicant's self-declared income. In both South Africa and Brazil, applicants declare their income and, if they are in the informal or subsistence economies or out of work, they are trusted to have told the truth. However, in South Africa, if applicants declare that they are employed, they are also asked to present their pay-slip while all applicants have to sign affidavits in which they declare they are telling the truth.[10] In Brazil, checks are made against a number of government databases, although this is only relevant for those in formal employment.[11]

There is no information available on the costs to government of undertaking means-tests, probably because of the difficulty of differentiating them from other administrative costs. But, given that minimal information is required form applicants, simple means-tests are likely to be relatively cheap to implement.

[8] Willmore (2007).

[9] Leite (2014) states that it is expensive to collect income data for all beneficiaries.

[10] Kidd et al (2018).

[11] Viana et al (2018).

2.2.2 Proxy means testing

The proxy means-test (PMT) methodology was developed in response to concerns that conventional means testing would be difficult in low- and middle-income countries since only a small proportion of the population are in the formal economy. Nonetheless, as Section 2.2.1 pointed out, some middle-income countries have chosen to implement means-tests anyway.

The PMT methodology tries to *predict* a household's – rather than an individual's – level of welfare using an algorithm that is commonly derived from statistical models.[12] Proxies for income are usually determined through an analysis of national household survey datasets and are meant to be easily observable and measurable indicators that have some correlation with consumption or income.[13] The proxies are commonly based on: demographics (such as age, number of people in the household, etc.); human capital (such as level of education of the household head); type of housing (such as the type of roof, walls, floor and toilet); durable goods (such as whether a household has a radio, refrigerator or television); and, productive assets (such as whether a household owns animals or land). A limited number of proxies are identified and weights are attached to each proxy depending on the strength of their correlation with consumption or income.

The selected proxies are developed into a scorecard which is administered to households by enumerators. In some countries, a census using the scorecard is undertaken of households and, ideally, all households in a country or the region where the programme is implemented should be included. However, this is challenging. For example, in Pakistan, the proxy means-test interviewed 85 per cent of households while, in Indonesia, only 40 per cent of households were covered. In contrast, in some countries, such as Georgia, households can apply to have the PMT scorecard administered on an on-demand basis. Occasionally, community-based targeting is combined with a PMT: communities make the initial selection of potential recipients of a scheme and the PMT survey is subsequently administered to that group.

Once the survey is undertaken, the data is fed into a computer and the algorithm is applied. Scores are allocated to households which are ranked from poorest to richest. The recipient households are selected if they have a qualifying score. Alternatively,

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[12] Proxy means-tests have been used to identify families rather than households, as in Pakistan's Benazir Income Support Programme (BISP). However, the assessment can only be based on the characteristics of households, since this is the unit employed in national household surveys.

[13] Occasionally, other methods for developing proxies are used without attempting to directly predict consumption or income. In Kenya, the World Bank used the national census to develop proxies (Villa 2016) while, in Zambia, Beazley and Carraro (2013) identified proxies only using assets. The mechanism for assessing people for India's Below Poverty Line card is a form of simple proxy means-test but was not developed using statistical analysis.

policymakers – or programme administrators – decide on a specific number of recipients and select those predicted to have the lowest incomes.

The PMT mechanism can be relatively expensive to implement. In Pakistan, the 2009 PMT survey cost US$60 million and Indonesia's cost US$100 million in 2015. In Tanzania, each PMT survey cost US$12 per household which means that, if it were to reach each household nationally, the total cost would be around US$140 million. Kenya's HSNP programme was particularly expensive, spending around US$10 million to survey only 380,000 households, or around US$26 per household.[14]

Further information on the PMT targeting mechanism can be found in Kidd and Wylde (2011), Kidd et al (2017) and Brown et al (2018).

2.2.3 Community-based targeting

Community-based targeting comprises a range of methodologies, some of which are very different in nature. These include:

- Community leaders or elites make the decision on who should benefit from a scheme.
- The entire community makes the decision in a large meeting, either with or without external facilitation (although, in reality, it is rare for everyone in the community to turn up to the meeting since they can take a long time and many people cannot afford the opportunity cost, while others in the community are socially excluded).
- Communities are given selection criteria by an external authority and are asked to select households based on those criteria. The selection could be undertaken by local elites and leaders, or in community meetings.
- Facilitators work with communities in a more intensive process, often engaging across smaller groups, to develop local criteria. The 'community' applies those criteria to rank households from 'poorest' to 'richest.'

There is no reliable information on the costs of community-based targeting. However, community-based targeting shifts some costs from governments to community members. When community members are obliged to spend a day or more in community meetings, the cumulative opportunity costs could be very high.[15] If facilitation by outsiders is also required, these costs can be considerable.[16] Indeed, Chinsinga (2005) argues that, in the

[14] Fitzgibbon (2014), Kidd (2017c) and World Bank (2016)
[15] McCord (2017).
[16] Kidd et al (2011) and McCord (2017).

context of Malawi, community-based targeting is too expensive a methodology for national-level implementation.

McCord (2017) provides a comprehensive overview of community-based targeting, discussing many of its challenges. However, her study offers limited evidence on its efficacy and none at all on its effectiveness when implemented at national scale. Indeed, community-based targeting is rarely implemented at national scale, although three examples are examined in this report: in Ethiopia, Rwanda and Vietnam.

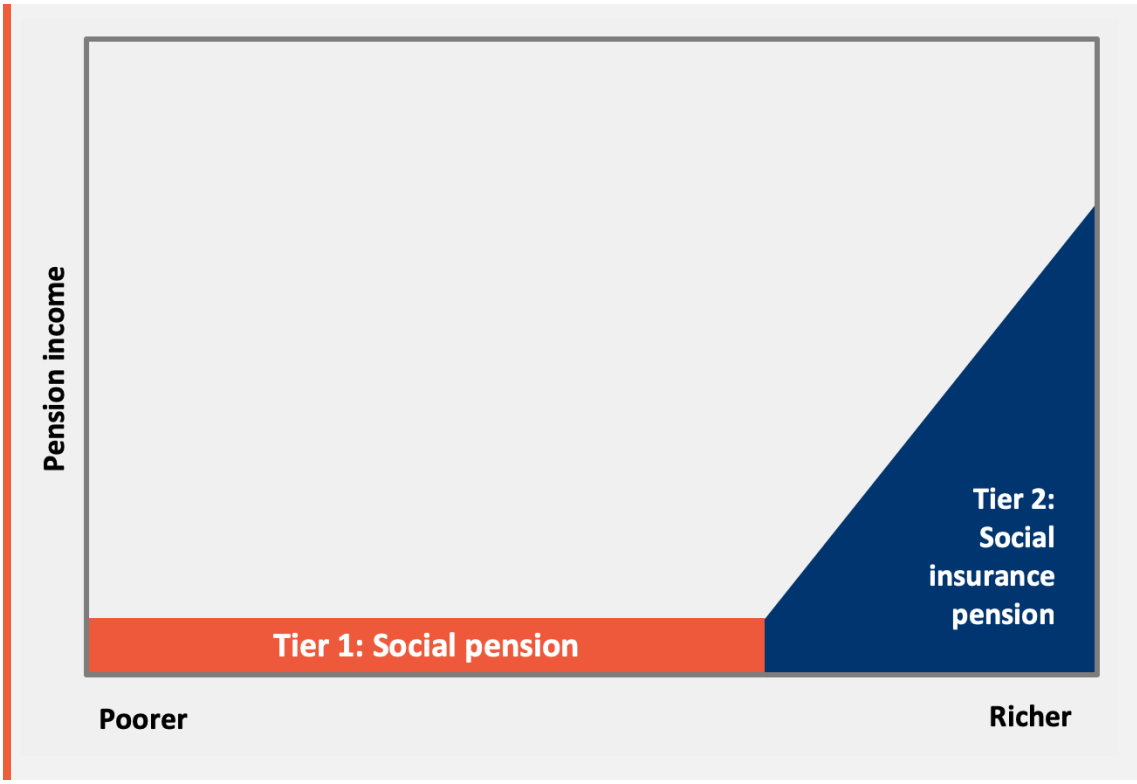
2.2.4 Self-targeting

With self-targeting, programmes are open to everyone with people making their own decision on whether to participate in the scheme. The methodology is commonly used in workfare schemes: usually a low wage is set for those participating in the scheme on the assumption that only the poorest will be willing to access it. So, while, in theory, the programme can be universal, its intention is to use the wage rate to discourage those who are better-off from participating. In effect, it should be understood as an attempt at a simple form of poverty targeting.

2.2.5 Benefit testing

Benefit testing is used by some governments to offer universal coverage although it could also be regarded as a simple form of income testing. For example, a tax-financed social pension is offered to all those not in receipt of another state pension (such as a social insurance or civil service pension). It should, in theory, offer universal pension coverage at a reduced cost to the state. Figure 2 shows how it should work, if performing effectively.

Figure 2: Diagrammatic representation of a pension system using benefit testing



Note: A state pension system using benefit testing comprises two tiers. The first tier consists of a tax-financed social pension which citizens are able to access if they do not receive any form of benefit from a social insurance pension at a certain minimum value. The tax-financed benefit is usually offered at a flat rate although there are examples of its value being lowered or gradually tapered among those with social insurance pensions. Therefore, a system using benefit testing aims to ensure universal pension coverage while guaranteeing a minimum income. Kidd (2015a) discusses benefit testing in more detail.

3 Methodology

This chapter outlines the methodology used in our research. First, it discusses the different options for measuring targeting effectiveness. It then provides a description of how the intended categories and recipients for schemes were understood and identified in the datasets and the steps taken in the data analysis. Annex 2 provides further information on the methodology.

3.1 Measuring targeting effectiveness

At the core of this study is a measure of the targeting effectiveness of social protection schemes. Other studies have made similar attempts to assess targeting effectiveness and a range of methods have been employed in the literature.[17] However, no one method has been used and, indeed, different methods can appear to give different results, which can cause confusion. It is not unusual for programmes to be assessed as being well-targeted when, in fact, the majority of the intended recipients have been excluded.

Often, the methods used to measure targeting effectiveness can include an inherent bias, resulting in poverty targeting appearing to perform better than it actually does. For example, a common method is to examine the proportion of all recipients of a scheme who are in the poorest 20 or 40 per cent of the population, a simple means of measuring benefit incidence. Yet, as Box 3 explains, this will, in most cases, mean that a poverty-targeted programme will appear to have more effective targeting than a universal scheme, even if it excludes most of the poorest households.

This study, therefore, aims to remove the bias by employing a simple and transparent methodology for assessing exclusion errors, following Coady, Grosh and Hoddinott's (2004) explanation of how to estimate exclusion and inclusion errors. As Figure 3 demonstrates, they used the coverage of a scheme as the basis for measuring errors.[18] So, the example given in Figure 3 has a population of 100 people – the intended category – and a scheme that intends to cover the poorest 40 per cent of the population. In effect, there would be 40 intended recipients. If, however, half of the intended recipients are excluded, the exclusion error would be 50 per cent; and, if half of the recipients are non-intended recipients, the inclusion error would be 50 per cent. In effect, therefore, when

[17] Cf. Coady et al. (2004); Devereux et al (2017); and, Brown et al. (2018)

[18] In their model, Coady et al (2004) used 'poor' and 'non-poor' as proxies for a scheme that targeted everyone who was 'poor,' who they assumed were 40 per cent of the population. In effect, therefore, they were measuring a scheme with coverage of 40 per cent of the population.

measuring targeting effectiveness against the intended coverage of a poverty-targeted scheme, the exclusion and inclusion errors should be the same.[19]

Figure 3: Calculation of exclusion and inclusion errors[20]

	Intended recipient	Non-intended recipient	Total
Excluded from scheme	20 Exclusion error = 50%	40 Correctly excluded	60
Included in scheme	20 Correctly included	20 Inclusion error = 50%	40
Total	40	60	100

Therefore, our methodology calculates the coverage of a scheme as a proportion of the category of the population for whom the programme has been designed, following the policy choice adopted. So, the intended category of the population for a child benefit comprises children of eligible age while the intended category for an old age pension is older people of eligible age. In the case of a scheme targeting 'poor households,' we assume that the intended category is all households in the country or region where the programme is operating.

[19] The exception is with universal selection. Take, for example, an old age pension intended for everyone aged 60 years and above. If no-one under 60 years is accessing the scheme but 10 per cent of those aged 60 years and over are not in receipt of the pension, the exclusion error is 10 per cent while the inclusion error is zero. In fact, if the 10 per cent who are not in receipt of the pension have been self-excluded, then it would be incorrect to call this an 'error.'

[20] Source: modified from Coady et al (2004). However, anyone reading Table 2.1 in Coady et al's paper should be aware that the authors miscalculated the numbers in the right-hand column of their table.

Box 3: The challenges of measuring targeting effectiveness using benefit incidence

Using benefit incidence to measure targeting effectiveness can disguise the failures of poverty targeting while making universal schemes appear ineffective. For example, a programme targeting 5 per cent of households may have 80 per cent of its recipients in the poorest 40 per cent of the population. This would be regarded by advocates of poverty targeting as an excellent performance. Yet, at the same time, it is possible that no-one in the poorest 5 per cent of the population is able to access the scheme and, overall, 90 per cent of those in the poorest 40 per cent of the population would be excluded. This is not an unusual scenario. For example, in Indonesia, the World Bank (2017b) claimed that 70 per cent of recipients of the *Program Keluarga Harapan* (PKH) scheme were in the poorest 40 per cent of the population yet, in another study, it found that 93 per cent of PKH's target population – at the time, 5 per cent of the population – were excluded (Alatas et al 2016). While the first result may look like 'effective targeting' the second appears to be particularly ineffective targeting.

An assessment using benefit incidence will make universal schemes look ineffective. For example, 40 per cent of recipients of a universal scheme with full coverage would, self-evidently, be in the poorest 40 per cent of the population. This may appear to be a worse performance than the poverty-targeted example given above, in which 80 per cent of recipients are in the poorest 40 per cent of the population. Yet, the universal scheme would, in contrast to the poverty-targeted example, also reach everyone in the poorest 40 per cent rather than excluding the majority. Assessing it from this perspective would make it appear particularly effective.

Coady, Grosh and Hoddinott's (2004) database on targeting effectiveness – which is often used as a reference point – used a variation on this methodology, resulting in a strong bias in favour of poverty targeting and against universal selection. However, their measure of targeting effectiveness – which was incorporated in their Table 3.3 – included a simple conceptual error which gave confusing results. While most programmes were assessed against the proportion of recipients in the poorest 40 per cent of the population, others were assessed against the poorest 20 per cent or the poorest 10 per cent. This meant that different programmes had different maximum scores: the majority, using 40 per cent, could not score more than 2.5 but those using 20 per cent could score up to 5 and those using 10 per cent could have a maximum score of 10. In effect, they ended up comparing apples, with pears, with oranges.

So, for example, 21 per cent of the recipients of Poland's Social Assistance Cash programme were in the poorest 10 per cent of the population – in other words, 79 per cent were excluded – but it was ranked as the 7th best targeted scheme, with a score of 2.1 (out of 10). It was just ahead of Romania's Minimum Income Guarantee, the 8th best targeted scheme: 83 per cent of its recipients were in the poorest 40 per cent of the population, with only 17 per cent excluded. Yet, it received a score of 2.08 (out of 2.5). The database is riddled with similar inconsistencies.

3.2 Identifying the intended category and recipients of schemes

We measure the exclusion and inclusion errors of each scheme against its coverage of the intended category (and, as explained above, by intended category, we mean that category of the population that has been chosen during Stage 1 of the targeting process, in effect the policy choice). So, we assume that the aim of the programme implementers – in most cases, the government – is to reach this proportion of the intended category, who we refer to as the intended recipients. So, for example, if a child benefit reaches 40 per cent of children, we assume that the intended recipients were 40 per cent of children. And, when a programme for 'poor households' reaches 20 per cent of all households, we assume that the intended recipients were 20 per cent of households.

However, we make an exception for universal schemes since their aim is to reach everyone within the intended category. In these cases, we assess exclusion errors against the entire category of the population – for example, all children in the case of a universal child benefit – rather than the actual coverage. Further, it should be noted that universal schemes – if well-implemented – do not have 'inclusion errors.'[21] If, for instance, the aim of a scheme is to reach all children and only 50 per cent of children live under the poverty line at the time of the household survey, it does not mean that the inclusion error is 50 per cent. Since the intention of policymakers is to incorporate all children within the scheme, the inclusion of 'non-poor' children is not an error, a point that is often poorly understood (see Box 4). Indeed, universal schemes frequently have aims that go beyond that of tackling poverty: for example, universal old

Box 4: Do universal lifecycle schemes have inclusion errors?

Some social protection specialists mistakenly believe that social protection is only for the poor and vulnerable and that anyone who is above the national poverty line should not be eligible for a scheme. As a result, they claim that, in a universal lifecycle scheme – such as a universal old age pension or child benefit – any recipient who is above the poverty line is an 'inclusion error.' For example, Devereux et al (2017) use the term 'inclusion error by design' to refer to recipients of a universal lifecycle scheme living above the poverty line, such as 'all people over 60 who receive a pension despite not being poor.' Yet, if the intention of the scheme is to provide everyone over 60 years of age with a pension, any inclusion of older people living above the poverty line cannot be an error. Furthermore, Devereux et al (2017) mistakenly assume that the national poverty line indicates all those who are 'poor' when, in reality, in most low and middle-income countries, the vast majority of the population is living in poverty using international poverty lines (see Section 6). And, they assume that poverty should only be determined at the household level when, in fact, many older people living in households above the poverty line do not themselves have any source of income and would qualify for individual means-tested schemes.

[21] An inclusion error within a universal scheme would happen when someone is included who does not meet the eligibility criteria. So, for example, if someone aged 63 years receives a universal pension with an age of eligibility of 65 years, that would be an inclusion error.

age social pensions are often seen as entitlements, given to people as a recognition of their contribution to society over their lifetimes. Further, if a programme is only implemented in a specific region of the country, the targeting effectiveness is assessed against the population in that region and not the national population (see Box 5).

Box 5: Geographic targeting?

Programmes are sometimes implemented in specific regions of a country, usually areas with higher indicators of poverty. This is often referred to as geographic targeting. In reality, in many cases, what appears to be geographic targeting is really just the initial phase of the national roll-out of a scheme or a pilot. In this study, we do not examine geographic targeting. However, in our analysis we take geography into account since, if programmes that are limited to a particular region are assessed against the national population, the results can distort or hide the effectiveness of the actual poverty targeting mechanism used within the geographic area. So, for example, the Hunger Safety Net Programme (HSNP) operates in four of the poorest counties in Kenya, where almost everyone lives in extreme poverty. If it were assessed at a national level, almost all recipients would be regarded as 'poor' and it would appear that the programme is effectively targeted. Yet, the result would be entirely driven by geography and not the targeting mechanism itself (in this case a mix of community-based targeting and a proxy means-test). Therefore, to determine the effectiveness of the HSNP's targeting mechanism – and any other programmes restricted to specific geographic regions – we assess them only against the population within the regions where they are operating.

3.3 Schemes and datasets included in the research

The research undertook analysis of 25 national household survey datasets and examined 42 social protection schemes or targeting registries (see Annex 1 for more information). The datasets were chosen on the basis of three criteria: i) we were able to gain access to the dataset; ii) it included a measure of household consumption or income so that household well-being could be determined; and, iii) it incorporated some means of identifying individuals or households who were accessing a social protection scheme or had been identified as eligible for social protection by a registry. As a result, we were unable to assess a number of social protection schemes because we either could not gain access to a relevant dataset or the information required was not available within the dataset. In particular, this resulted in us not being able to assess many social protection schemes in Africa. Other schemes were excluded after we had undertaken the analysis because the number of recipient households identified was too small for a reliable assessment or we were unable to identify accurately the intended category.[22] Table 1 sets out the schemes and registries that were examined as well as the datasets used.

[22] The schemes excluded were: the *Asignación Universal por Hijo* in Argentina because it was not possible to identify the children who were eligible; the *Benefício de Prestação Continuada* in Brazil because, similarly, we could not identify the older people and people with disabilities who were eligible; the Cash Transfer for Orphans and Vulnerable Children and Older Persons Cash Transfer in Kenya because there were not sufficient recipient households identified; and, the Social Cash Transfer in Malawi because, again, the number of recipient households was too small.

Table 1: List of schemes incorporated in the research

Country	Scheme	Intended category and recipients	Coverage (as percentage of intended category)	Survey Dataset	Programme Type
		Universal Selection			
Bolivia	*Renta Dignidad*	Adults aged 60 years and over	92	EH 2015	Old Age Pension
Bolivia	*Bono Juancito Pinto*	Children attending public primary schools for formal education, youth alternative and/or special education	92	EH 2015	School stipend
Georgia	Old Age Pension	Women aged 60 years and over and men aged 65 years and over	99	WMS 2015	Old Age Pension
Mongolia	Child Money Programme	Children	98	HSES 2016	Child benefit
		Means Testing			
Albania	*Ndihme Ekonomike*	Families living in poverty	8	LSMS 2012	Poor relief
Bangladesh	Old Age Pension	Women aged 62 years and above and men aged 65 years and above, living in poverty	18	HIES 2016	Old Age Pension
Brazil	*Bolsa Família*	Families living in poverty or extreme poverty	14	PNAD 2017	Poor relief CCT
South Africa	Child Support Grant	Children in low income families	71	GHS 2017	Child benefit
South Africa	Old Age Grant	Adults aged 60 years and over with low incomes and/or assets valued below a specified threshold and not receiving any other social grant	84	GHS 2017	Old Age Pension
Sri Lanka	*Samurdhi*	Households living in poverty	19	HIES 2016	Poor relief
Sri Lanka	Senior Citizens' Allowance	Households with adults aged 70 years and above, living in poverty	23	HIES 2016	Old Age Pension
Uzbekistan	Childcare Allowance	Households with children aged between 0 and 1 year living in poverty	23	L2CU 2018	Poor relief

Uzbekistan	Family Allowance	Households with children aged between 2 and 14 years living in poverty	8	L2CU 2018	Poor relief
Uzbekistan	Low-Income Allowance	Households living in poverty	1	L2CU 2018	Poor relief
		Proxy Means Testing			
Armenia	Family Benefits	Families with children living in poverty	19	HILCS 2015	Poor relief
Colombia	*Familias en Acción*	Households with children living in poverty	23	ECV 2017	Poor relief CCT
Colombia	*Programa Colombia Mayor*	Women aged 54 years and over and men aged 59 years and over, living in poverty	19	ECV 2017	Old Age Pension
Ecuador	*Bono de Desarrollo Humano*	Households living in poverty with children aged 16 years and under	18	ENCV 2014	Poor relief CCT
Ecuador	Social Pension	Adults aged 65 years and over living in poverty	46	ENCV 2014	Old Age Pension
Georgia	Targeted Social Assistance	Families living in poverty	15	WMS 2015	Poor relief
Ghana	Livelihood Empowerment Against Poverty	Households living in poverty	1	GLSS7 2017	Poor relief
Guatemala	*Mi Bono Seguro*	Families living in poverty or extreme poverty with children aged 15 years and under	7	ENCOVI 2014	Poor relief CCT
India	Indira Gandhi National Old Age Pension Scheme	Adults aged 60 years and above, living in poverty	21	IHDS 2012	Old Age Pension
India	Below Poverty Line	Households living in poverty	36	IHDS 2012	Registry
Indonesia	*Program Keluarga Harapan*	Households with children and/or pregnant or lactating women living in poverty	7	SUSENAS 2017	Poor relief CCT
Indonesia	*Kartu Perlindungan Sosial*	Households living in poverty	14	SUSENAS 2017	Registry
Indonesia	*Pintar*	Children aged between 6 and 17 years living in poverty and attending school	18	SUSENAS 2017	School stipend
Kenya	Hunger Safety Net Programme	Households in Northern Kenya living in poverty	20	KIHBS 2015	Poor relief
Mexico	*Prospera*	Households living in poverty	18	ENIGH 2016	Poor relief CCT
Pakistan	Benazir Income Support Programme	Families living in poverty	8	HIES 2015	Poor relief

Peru	*Juntos*	Households with children aged 18 years and under and/or pregnant and breastfeeding women who are living in poverty	16	ENAHO 2017	Poor relief CCT
Philippines	*Pantawid Pamilyang Pilipino Program*	Households with children aged 18 years and under and/or pregnant women living in poverty	23	APIS 2014	Poor relief CCT
Uruguay	*Asignaciones Familiares*	Families with children aged 17 years and under and/or people with disabilities living in poverty	45	ECH 2016	Poor relief CCT
		Community-based Targeting			
Ethiopia	Productive Safety Net Programme (direct support)	Chronically food insecure households in rural Ethiopia that are labour constrained	8	ESS 2015	Poor relief
Ethiopia	Productive Safety Net Programme (public works)	Chronically food insecure households with labour capacity in rural Ethiopia	9	ESS 2015	Workfare
Rwanda	*Vision 2020 Umurenge Programme* (public works)	Households living in poverty with labour capacity	2	EICV 2014	Workfare
Rwanda	*Vision 2020 Umurenge Programme* (direct support)	Households living in poverty that are labour constrained	10	EICV 2014	Poor relief
Rwanda	*Ubudehe* (groups 1 and 2)	Households living in poverty	30	EICV 2014	Registry
Vietnam	Poor List	Households living in poverty	11	VHLSS 2014	Registry
		Self-Targeting			
India	National Rural Employment Guarantee Act 2005	Adult members of households in rural India	29	IHDS 2012	Workfare
		Benefit Testing			
Mexico	*Programa 65 y más*	Adults aged 65 years and over not in receipt of another state pension	60	ENIGH 2016	Old Age Pension
Vietnam	Social Pension 80+ years	Adults aged 80 years and over not in receipt of another state pension	52	VHLSS 2016	Old Age Pension

3.4 Data analysis methodology

The methodology employed in the data analysis incorporated the following steps:

- Identifying in the household surveys those households with members in the intended category, following a review of programme documentation.
- Identifying recipients and their households in the household survey dataset which enabled us to estimate coverage across households incorporating members from the intended category.
- Subtracting from the total household consumption or income the value of the transfer received, to determine the pre-transfer well-being of households (see Box 6).[23] In some cases, information on the value of the transfer received was in the dataset while, in other cases, we imputed the value of the transfer based on information we obtained from other reliable sources.
- Ranking the households with a member in the intended category from poorest to richest according to per capita pre-transfer consumption or income.
- Identifying the proportion of households including an intended recipient in each percentile of the intended category that accessed the scheme or were identified by a registry as eligible for social protection.

Box 6: Rationale for the use of consumption or income to measure well-being in the analysis

There is significant debate on the best means to determine the well-being of individuals and households, with the use of consumption and/or income being challenged as too narrow. Many would argue for multidimensional measures of well-being. However, in our analysis we have used consumption and/or income for the reason that the main aim of social security schemes is to increase the income of individuals, families and households. Indeed, as indicated earlier, poverty targeting is often synonymous with income testing. By using consumption and/or income, we are following conventional methods of assessing targeting effectiveness.

By employing this methodology, it was possible to assess targeting effectiveness using two measures:

- Identifying the proportion of households with a member from the intended category that are incorrectly excluded or correctly included in the scheme, when measured against a scheme's intended recipients (in other words, the inclusion and exclusion errors). This was described in Section 3.1.
- Measuring the effectiveness of programmes in reaching the poorest 20 per cent of the intended category, again using households as the unit of analysis. The metric

[23] Annex 2 shows whether analysis of the household survey dataset employed consumption or income data and the assumptions used to estimate pre-transfer estimates of consumption or income.

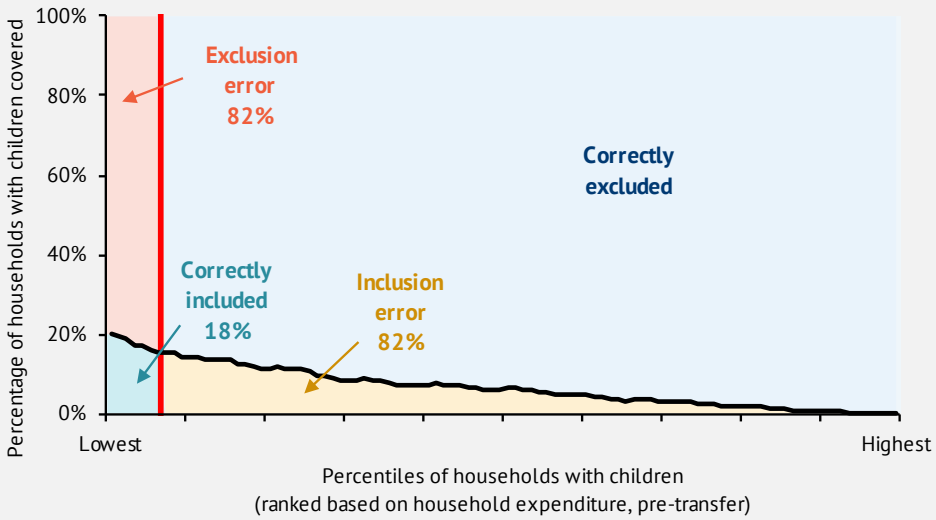
used is the percentage of the poorest 20 per cent of households with a member from the intended category who are excluded from the scheme.

In addition to calculating inclusion and exclusion from schemes, the coverage of recipients by specific schemes has also been represented diagrammatically in Chapter 5. Box 7 describes how the graphs found in Chapter 5 should be interpreted.

Box 7: How to interpret the targeting effectiveness graphs found in Chapter 5

Figure 4 shows an example of one of the graphs used in the report for single schemes, to demonstrate their targeting effectiveness. On the X axis, the intended category of the population is ranked by percentile, from poorest to wealthiest households, while the Y axis indicates the scheme's coverage across each percentile of the intended category.[24] Therefore, those under the black line in the graph are included in the scheme while those above the black line are excluded from the scheme. The red line indicates the actual – in other words, intended – coverage of the scheme as a percentage of the intended category: so, all households to the left of the red line are the scheme's intended recipients within the intended category while those to the right of the red line should not be able to access it. Each graph shows the exclusion error of the scheme – when measured against the intended recipients – as well as the inclusion error. Schemes using universal selection and benefit testing do not have a red line since coverage is meant to be everyone within the intended category.

Figure 4: Example of a targeting effectiveness diagram (*Program Keluarga Harapan*, Indonesia)



[24] To smooth fluctuations of coverage estimates across percentiles, the black line is a rolling average curve of the coverage for each percentile (see Annex 2). Each point in the curve is a simple average of the coverage estimate in that percentile in addition to the coverage estimates of the adjacent four percentiles (two to each side).

4 Global overview of the effectiveness of targeting approaches

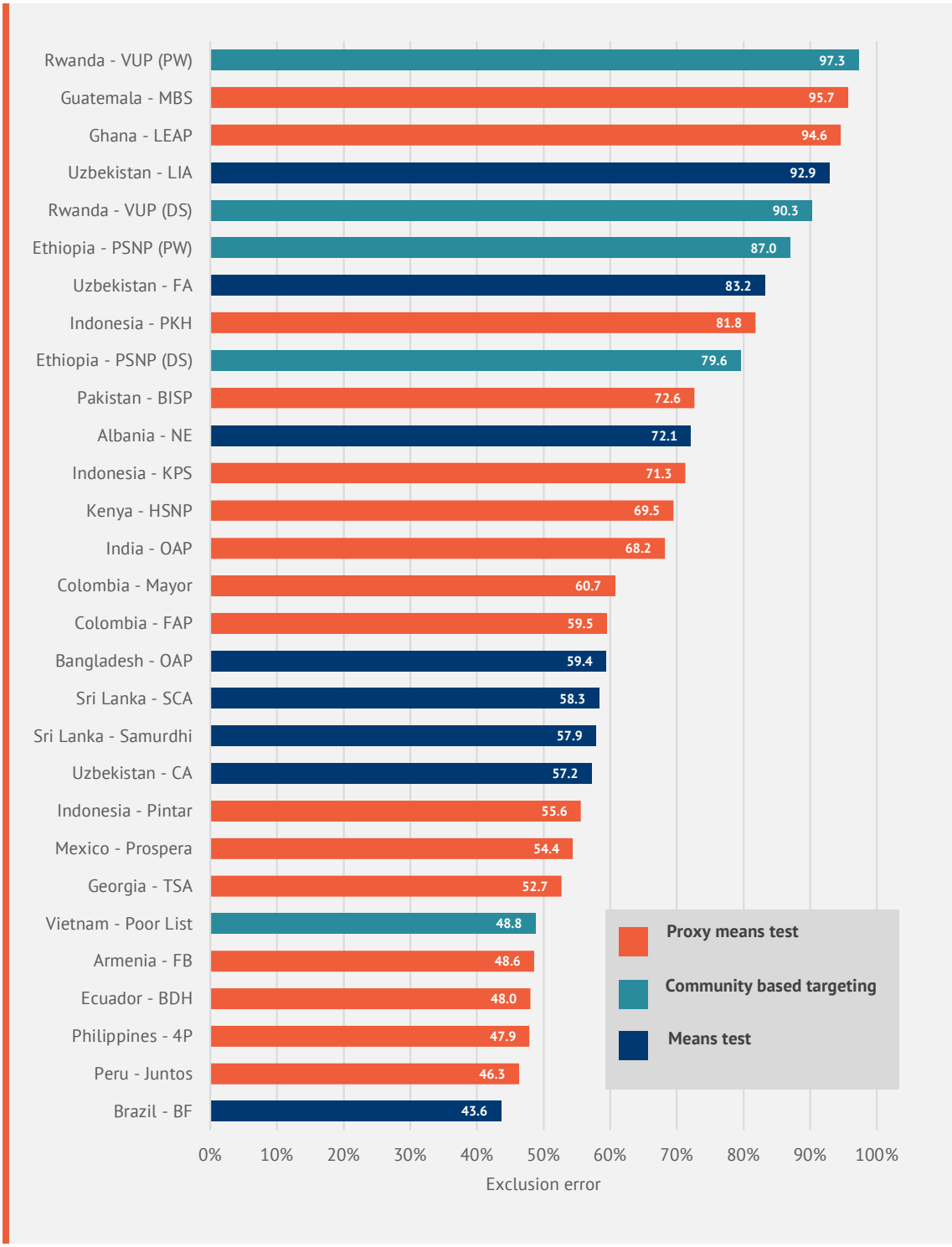
This chapter offers a global overview of the results of the analysis while Chapter 5 presents a more in-depth analysis of each type of targeting mechanism and individual scheme. The first section in this chapter examines the effectiveness of programmes that specifically use poverty targeting to identify the poorest members of society. Section 4.2 compares all of the schemes in our analysis – including, in addition to poverty-targeted schemes, those that are universal or have higher coverage – focusing in particular on their exclusion errors when measured against their intended recipients and their effectiveness in reaching the poorest 20 per cent of their intended category.

4.1 The effectiveness of poverty targeting

As indicated in the introduction, one of the aims of the research was to assess the effectiveness of poverty-targeted programmes in reaching their intended recipients as well as those living in extreme poverty. In other words, we wanted to assess whether it is possible to effectively reach those living in extreme poverty using poverty targeting. To answer this question, we examined the targeting effectiveness of those programmes aiming to reach the poorest 25 per cent or less of their intended category.

Figure 5 shows the exclusion errors of poverty-targeted schemes when measured against their effectiveness in reaching their intended recipients. Across all programmes, errors are high. Brazil's *Bolsa Família* scheme – which uses a simple means-test – has the most effective targeting, yet still excludes 44 per cent of its intended recipients. The worst performing programme is Rwanda's *Vision 2020 Umurenge Programme* (VUP) which used community-based targeting and had an exclusion error of 97 per cent. In other words, for every 36 households in the programme's target group, only one could access the programme. It was closely followed by Guatemala's *Mi Bono Seguro* scheme, which employs a proxy means-test and had an error of 96 per cent among intended recipients.

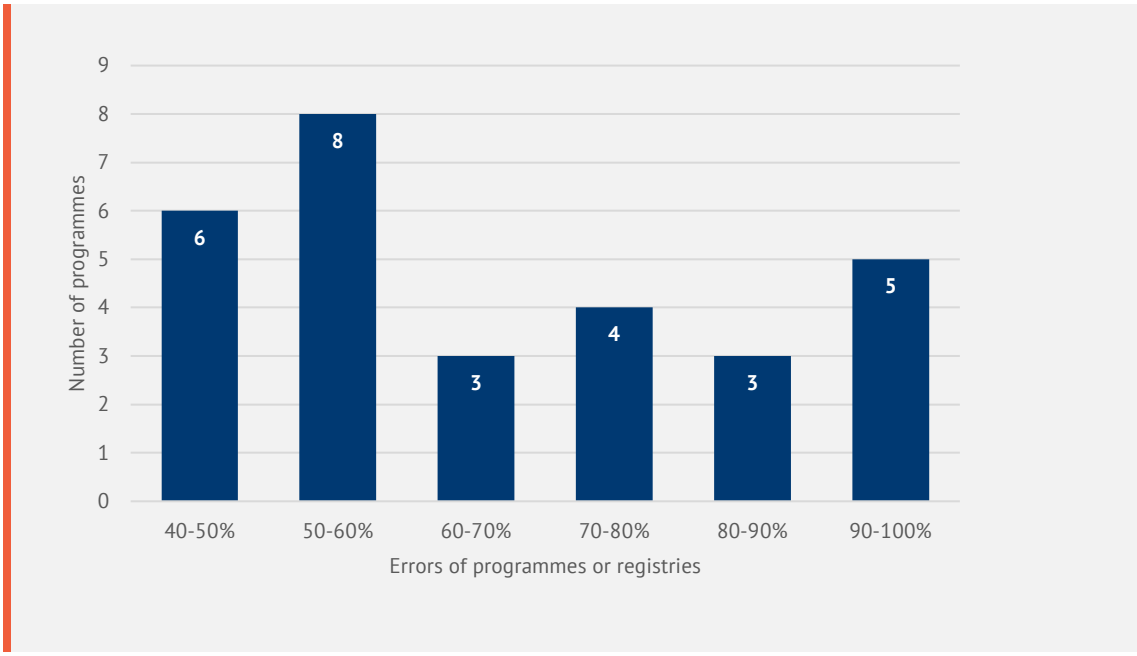
Figure 5: Exclusion errors for social protection programmes targeting the poorest 25 per cent of their intended category or less



Source: own calculations using the national household surveys described in Table 1. Note: see Annex 2 for a detailed description of the methodology.

In fact, out of 29 programmes or registries with coverage under 25 per cent of their target population, 12 have exclusion errors above 70 per cent, 8 have errors above 80 per cent and 5 have errors above 90 per cent. On the other hand, only six were able to reach over half of their intended recipients: Brazil's *Bolsa Família*, Peru's *Juntos*, the Philippines' *Pantawid*, Ecuador's *Bono de Desarrollo Humano*, Armenia's Family Benefits and Vietnam's Poor List. All other programmes excluded more than half of their intended population. Figure 6 summarises the number of schemes with different ranges of errors.

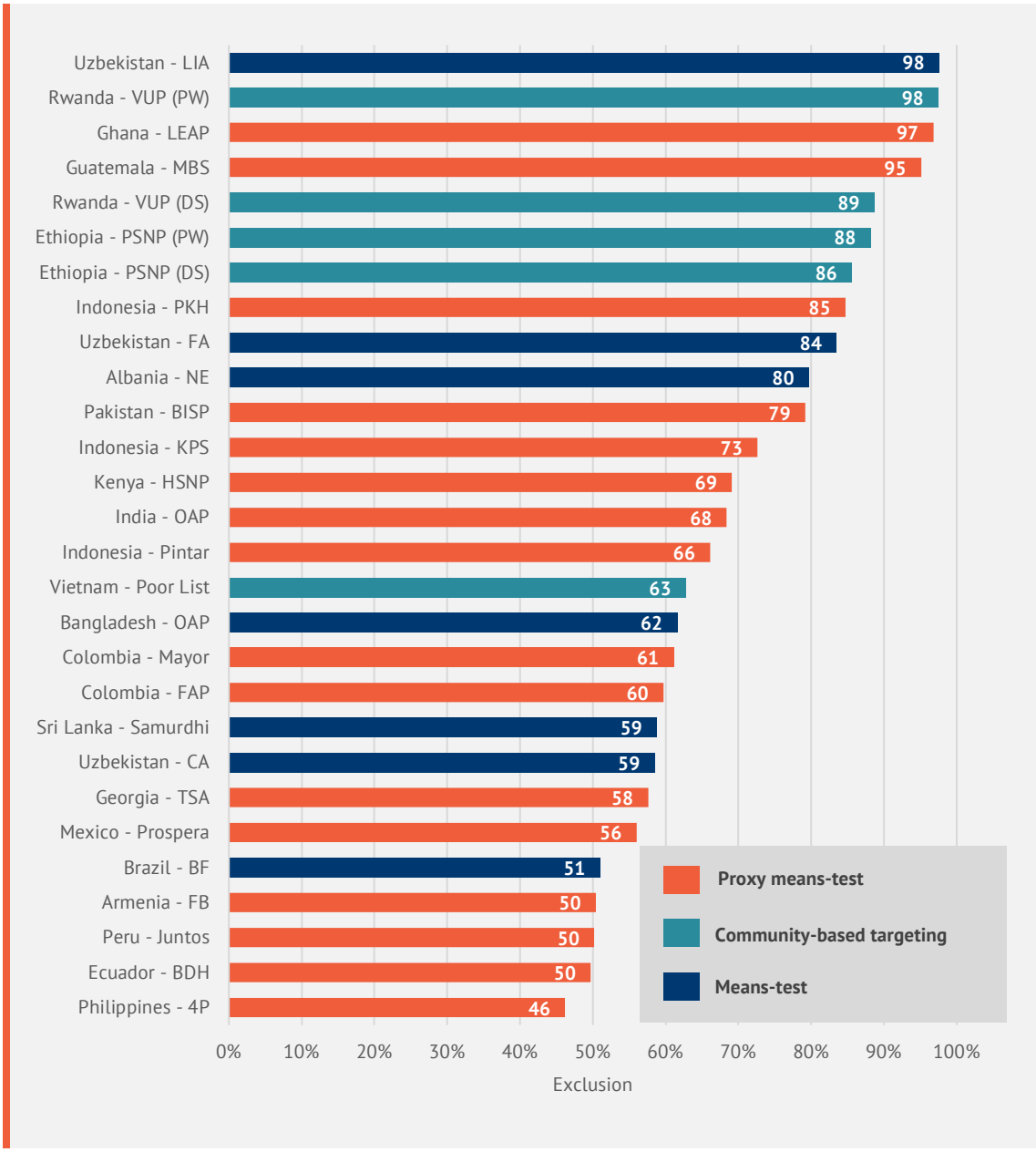
Figure 6: Distribution of the magnitude of errors for 25 poverty-targeted schemes in the research



A similar pattern is found when poverty-targeted schemes are assessed in terms of their effectiveness in reaching the poorest 20 per cent of their intended category. In the case of those programmes with coverage below 20 per cent of their intended category, this measure combines both targeting errors and undercoverage. Therefore, schemes with coverage below 20 per cent – which, to a degree, indicates limited political support – will necessarily exclude some of those in the poorest 20 per cent.

As Figure 7 indicates, only one programme manages to reach over half of the poorest 20 per cent within its intended category: the Philippines' *Pantawid* programme, which reaches 46 per cent. Therefore, consistently, poverty-targeted schemes are excluding over half of the poorest quintile of their intended category. Uzbekistan's Low-Income Allowance and Rwanda's VUP public works programme are the worst performing programme, with errors of 98 per cent.

Figure 7: The proportion of those in the poorest 20 per cent of the intended category excluded from schemes



Source: own calculations using the national household surveys described in Table 1. Note: see Annex 2 for a detailed description of the methodology.

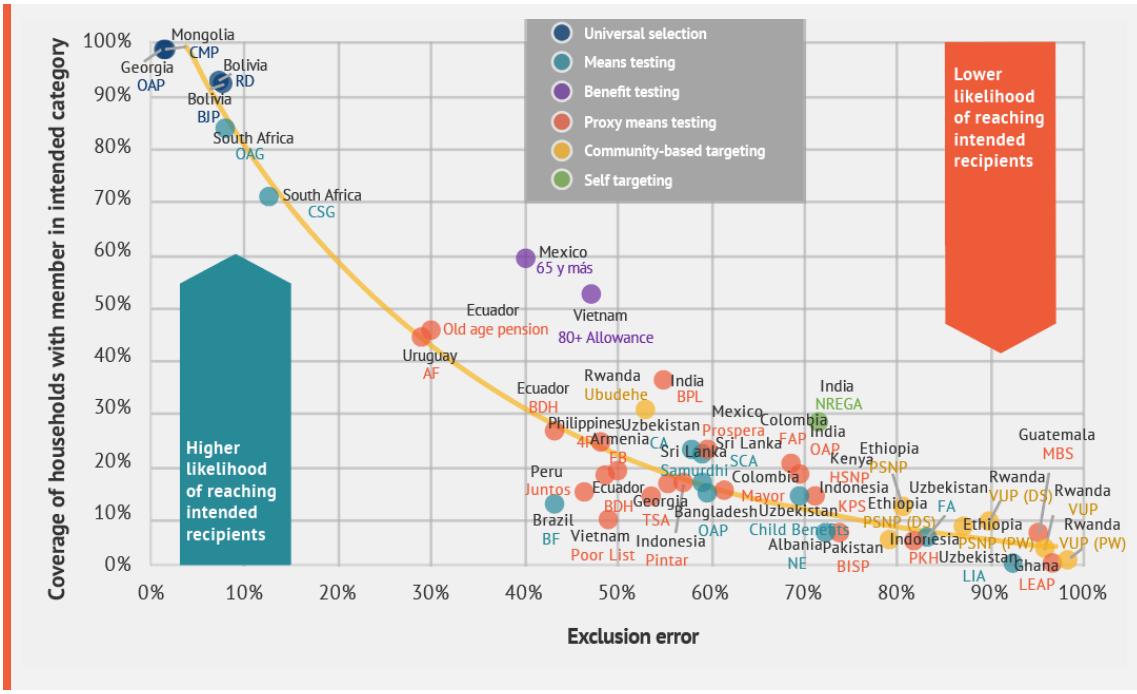
Overall, the results demonstrate a mass failure of poverty targeting across low- and middle-income countries. In programme after programme, the majority of both the intended recipients and the poorest members of society are excluded. Therefore, if the aim of governments and international agencies is to reach those living in poverty and 'leave no-one behind,' the use of poverty targeting will result in failure.

4.2 The relationship between the coverage of schemes and targeting effectiveness

Of course, as discussed above, not all schemes are targeted at the poorest members of society. Many schemes have higher coverage with some offering universal access. This section examines whether higher coverage schemes – including those employing a universal approach – are more effective than poverty-targeted programmes in reaching both their intended recipients and those living in extreme poverty.

Figure 8 maps the coverage of schemes against their exclusion errors, when measured against their intended recipients. As would be expected, it shows that there is a strong relationship between higher coverage and lower exclusion of the intended recipients (indeed the correlation coefficient is -0.80). In the top left-hand corner of the graph, there is a small cluster of universal schemes which have exclusion errors below 10 per cent. In fact, in the case of Georgia's universal Old Age Pension and Mongolia's universal Child Money scheme, errors are below 2 per cent, both highly effective performances.

Figure 8: Relationship between coverage and exclusion errors measured against intended recipients



Source: own calculations using the national household surveys described in Table 1. Note: see Annex 2 for a detailed description of the methodology.

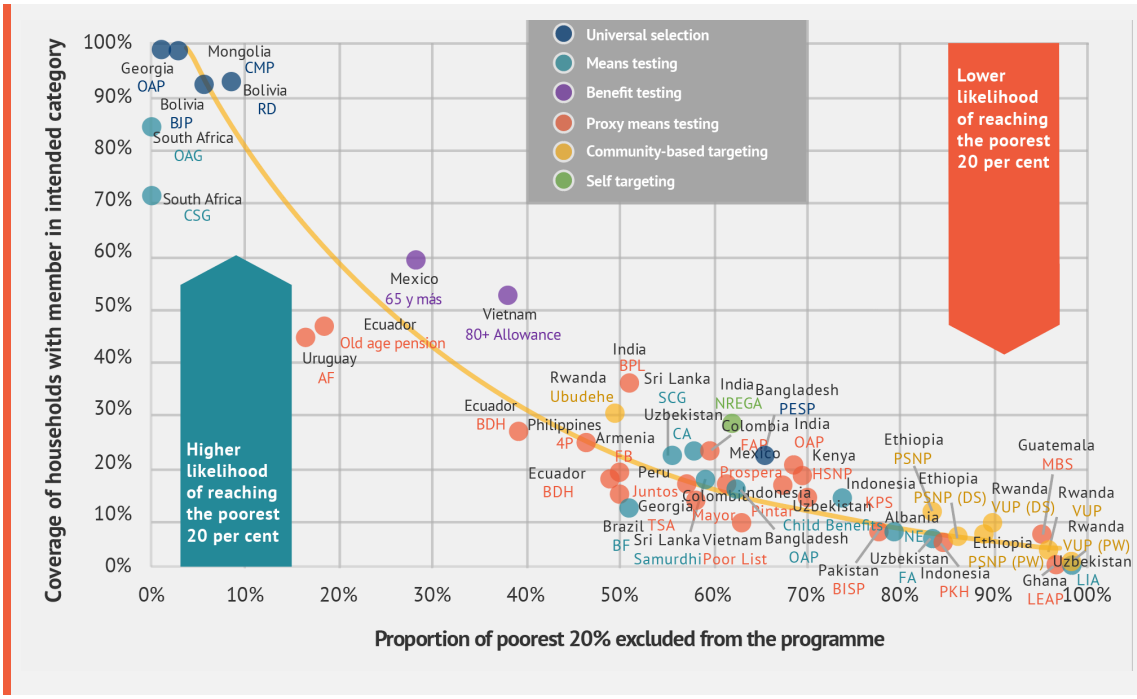
South Africa's social grant schemes have relatively high coverage – though not fully universal – reaching over 70 per cent of their intended categories (children and older people). While they do not perform as well as universal schemes, their exclusion errors are much lower than programmes targeted at the poorest members of society: the Old Age Grant's exclusion error is 8 per cent while it is 13 per cent for the Child Support Grant. Uruguay's *Asignaciones Familiares* programme has lower coverage so, unsurprisingly, its exclusion error is higher, at 29 per cent of intended recipients, but still better than schemes targeted at those living in extreme poverty.

As indicated in Section 4.1, poverty-targeted schemes have the highest exclusion errors. Nonetheless, within poverty-targeted schemes, there is a similar correlation between higher coverage and lower errors. Therefore, those with the lowest coverage – such as Ghana's LEAP programme, Uzbekistan's Low-Income Allowance and the VUP Public Works programme in Rwanda – exclude the vast majority of their intended recipients. As coverage expands, errors among poverty-targeted schemes tend to reduce, though they remain high.

It is interesting to compare countries that have adopted more than one targeting mechanism. Georgia's universal Old Age Pension is, as indicated earlier, very successful, with exclusion errors of only 1.4 per cent. In contrast, its Targeted Social Assistance (TSA) poor relief programme – which is aimed at households living in poverty and uses a proxy means-test – has exclusion errors of 53 per cent. Similarly, in Mexico, the benefit-tested *Programa 65 y Más* old age scheme is much more effective than the well-known, but recently disbanded, *Prospera* programme.

Figure 9 adopts a slightly different approach to assessing targeting effectiveness, comparing how well programmes perform in reaching the poorest 20 per cent of the population within their intended categories. As found with exclusion errors, the higher a scheme's coverage, the greater its effectiveness in reaching the poorest members of society (the correlation co-efficient between coverage and the exclusion of the poorest 20 per cent is -0.83). Universal and high coverage schemes perform particularly well, with exclusion below 10 per cent (in other words, over 90 per cent of the poorest 20 per cent are included). In fact, three schemes – Georgia's Old Age Pension and South Africa's Old Age and Child Support Grants – have no measurable error, while Mongolia's universal Child Money scheme reaches 99 per cent of the poorest 20 per cent of children. In contrast, as discussed earlier, poverty-targeted schemes – which, ironically, aim to reach those living in extreme poverty – are much less effective than universal schemes, with almost all excluding over half of the poorest 20 per cent of their target populations.

Figure 9: Relationship between coverage of schemes and the exclusion of the poorest 20 per cent of intended categories



Source: own calculations using the national household surveys described in Table 1. Note: see Annex 2 for a detailed description of the methodology.

It is possible to determine which programmes are performing better than expected and those doing worse: those schemes below the trend line are performing better than average while those above it are below average. There is no consistent pattern so it is not possible to definitively conclude that one poverty targeting mechanism is superior to others. Certainly, investing significant sums in proxy means-tests does not necessarily result in better than average performance, as evidenced by Colombia's and Indonesia's schemes and Kenya's Hunger Safety Net Programme (HSNP).

5 Targeting effectiveness across individual schemes and registries

As indicated earlier, the research examined targeting effectiveness across 42 schemes. The detailed results for each of these schemes are presented in this chapter, while Annex 1 provides a comprehensive overview of the results.[25] This chapter begins by examining universal schemes before moving onto an examination of income testing, evaluating each mechanism in turn: means testing, proxy means testing, community-based targeting, self-targeting and benefit testing.

5.1 Universal schemes

The research examined four universal schemes: Georgia's Old Age Pension, Mongolia's Child Money programme and Bolivia's *Renta Dignidad* social pension and the *Bono Juancito Pinto* scheme, a stipend for children in the first 8 years of public school. The results for each scheme are set out in Table 2.

Table 2: Summary of the results from programmes offering universal coverage

Country	Scheme	Coverage (as percentage of intended category)	Targeting Error	
			Exclusion errors with respect to intended recipients (percentage)	Exclusion of those in bottom 20% (percentage)
Bolivia	*Renta Dignidad*	92	8	8
Bolivia	*Bono Juancito Pinto*	92	8	6
Georgia	Old Age Pension	99	1	0
Mongolia	Child Money programme	98	2	1

Source: own calculations using the national household surveys described in Table 1. Note: see Annex 2 for a detailed description of the methodology.

[25] The analysis also looked at the targeting effectiveness of three combined schemes: Ethiopia's combined direct support and workfare schemes within PSNP; Rwanda's combined direct support and workfare schemes within VUP; and, Uzbekistan's Family and Childcare Allowances combined poor relief schemes.

Two of the universal schemes – Georgia's Old Age Pension and Mongolia's Child Money programme – have been remarkably successful in reaching almost all their intended recipients. The exclusion errors are 1 and 2 per cent respectively while the exclusion of those in the poorest 20 per cent is zero and 1 per cent. In fact, in Georgia's pension, any exclusion is mainly among those near the top of the welfare distribution suggesting some self-exclusion, perhaps because people felt that they did not need the scheme.

Both of Bolivia's schemes demonstrate that, while universal schemes are much more effective than poverty targeting in reaching the poorest members of society, it should not be assumed that no-one will be excluded. Errors are 8 per cent for both the *Renta Dignidad* pension and *Bono Juancito Pinto* programmes. As Panels a) and b) in Figure 10 indicate, the level of exclusion is similar across the welfare distribution. It is not possible to ascertain from the dataset the reasons for the exclusion.

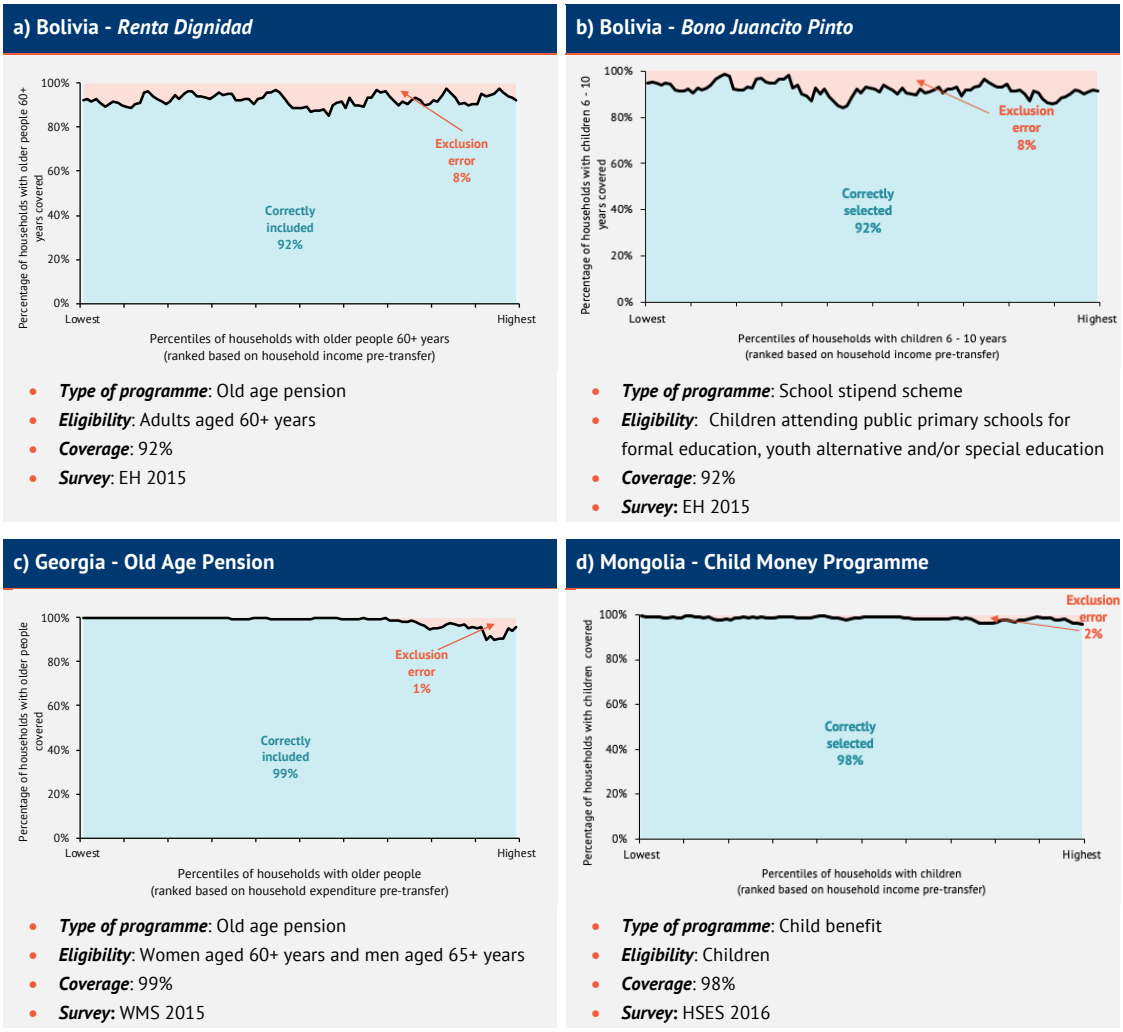
Nonetheless, within universal schemes potential causes of exclusion include: some people may not have heard about the schemes or may not have the required documentation, such as identity cards or birth certificates; people with disabilities may find it challenging to apply for the schemes; or, as in Georgia, there is always likely to be some self-exclusion among those at the top of the welfare distribution who do not require the additional income.[26] The first two of these reasons would, of course, also apply to poverty targeting.

Given that universal schemes appear to be very effective in reaching the poorest members of society, it is strange that they are opposed by some organisations with mandates to reduce poverty. Both the World Bank and IMF have, in recent years, attempted numerous times to persuade governments across the world to target universal social protection schemes.[27] For instance, despite the World Bank observing that Mongolia's Child Money programme is 'effectively reaching the poor,' it nonetheless joined with the International Monetary Fund (IMF) and Asian Development Bank in 2018 to force the Government of Mongolia to target the scheme, almost certainly increasing the exclusion of children living in poverty.

[26] Kidd (2017c) and Kidd et al (2019b).

[27] Kidd (2017d; 2018a; 2018b).

Figure 10: Targeting effectiveness of universal schemes



Source: own calculations using the national household surveys described in Table 1. Note: see Annex 2 for a detailed description of the methodology.

5.2 Poverty targeting

This section examines five mechanisms using some form of poverty targeting: means testing, proxy means testing, community-based targeting, self-targeting and benefit testing.

5.2.1 Means testing

The research examined means testing in six countries: Albania, Bangladesh, Brazil, South Africa, Sri Lanka and Uzbekistan. Uzbekistan's mean test is, however, combined with a degree of community-based targeting since decisions on selection are made by voluntary local committees, known as *Mahallas*.

The results on the effectiveness of the means-tests are set out in Table 3. Contrary to many people's expectations, means testing can perform relatively well in middle-income countries. As indicated in Section 4.1, among those programmes targeted at the poorest members of society – in other words, with coverage below 25 per cent – Brazil's *Bolsa Família* programme is the best performing, with an exclusion error of 44 per cent. However, as Panel c) of Figure 13 shows, it appears to be less successful in reaching the very poorest, with 48 per cent of the poorest 5 per cent of the targeted population excluded.

Table 3: Summary of the results from programmes using means testing[28]

Country	Scheme	Coverage (as percentage of intended category)	Targeting Error	
			Exclusion errors with respect to intended recipients (percentage)	Exclusion of those in bottom 20% (percentage)
Albania	*Ndihme Ekonomike*	8	72	80
Bangladesh	Old Age Pension	18	59	62
Brazil	*Bolsa Família*	14	44	51
South Africa	Child Support Grant	71	13	0
South Africa	Old Age Grant	84	8	0
Sri Lanka	*Samurdhi*	19	58	59
Sri Lanka	Senior Citizens' Allowance	23	58	57
Uzbekistan	Family and Childcare Allowances	14	71	69
Uzbekistan	Childcare Allowance	23	57	58
Uzbekistan	Family Allowance	8	83	83
Uzbekistan	Low-Income Allowance	1	93	98

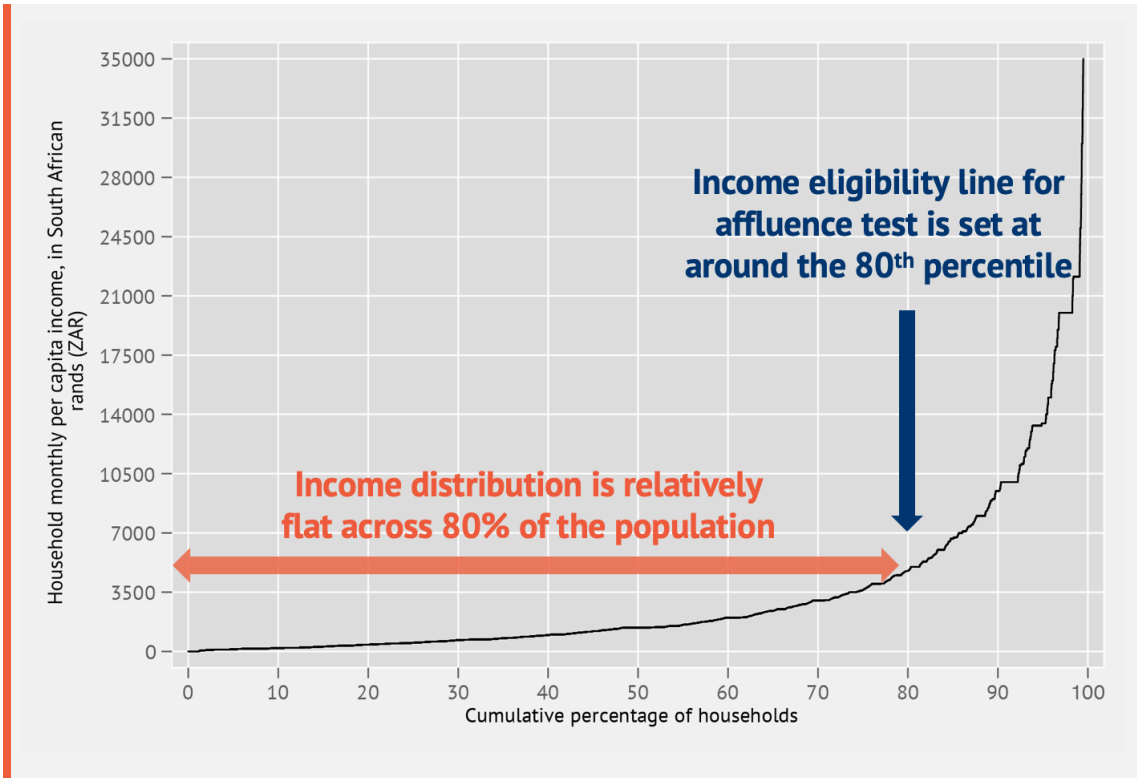
Source: own calculations using the national household surveys described in Table 1. Note: see Annex 2 for a detailed description of the methodology.

South Africa's success with its means-test is probably because it is attempting to exclude the richest, which is easier than identifying those living in extreme poverty. As Figure 11 indicates, incomes are relatively flat across 80 per cent of the population and greater differentiation is found only among the richest 10 per cent. Further, the South African Social Security Agency (SASSA), which implements the schemes, undertakes checks on the incomes of public servants, many of whom are in the top quintile of the population. This

[28] The results for Uzbekistan are taken from Kidd et al (2019a), where the analysis was also undertaken by Development Pathways.

probably dissuades many from applying. The exclusion errors can be explained by a number of reasons, not necessarily linked to the means-test: for example, many children are excluded from the Child Support Grant because they do not have birth certificates; a high proportion of the white population does not apply for the Child Support Grant because they believe it is not for them; and, some people living with disabilities find it challenging to overcome barriers when applying for the programmes.[29]

Figure 11: Distribution of incomes across South Africa's population



Source: own calculations using the GHS 2017.

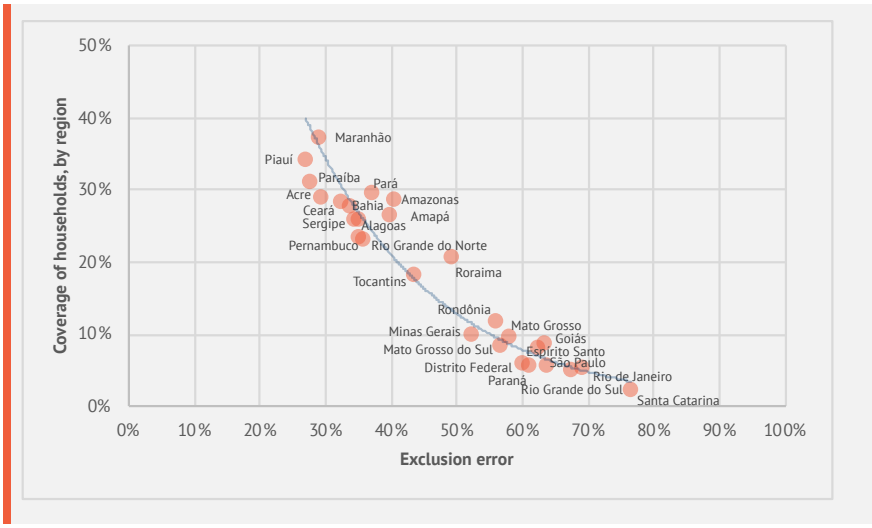
Brazil's relative success with *Bolsa Familia's* targeting is probably not due to the means-test itself, given that it is directed at the poorest members of society among whom there are minimal differences in incomes. Rather, it is likely to be caused by the scheme's use of quotas. Each municipality in the country is given a specific quota of *Bolsa Família* beneficiaries, which is based on the absolute numbers of households living in poverty in each municipality.[30] Therefore, the poorer the region, the higher the proportion of recipients: for example, in the North-East of the country – where poverty levels are high – 28 per cent of households are recipients while, in the wealthier South, less than 5 per

[29] Further information on the challenges people face in accessing South Africa's social security schemes can be found in: UNICEF and SASSA (2013); Kidd (2017c); Kidd et al (2018).

[30] Viana et al (2018).

cent are recipients. And, as Figure 12 shows – and in line with the international pattern – coverage has also a strong negative correlation with errors: the lower the coverage, the less effective the means-test, and vice versa (the correlation coefficient is -0.96). So, in some regions of the country, exclusion errors are above 60 per cent, reaching almost 80 per cent in Santa Catarina.

Figure 12: Relationship between coverage and exclusion errors across states in Brazil for the *Bolsa Família* programme

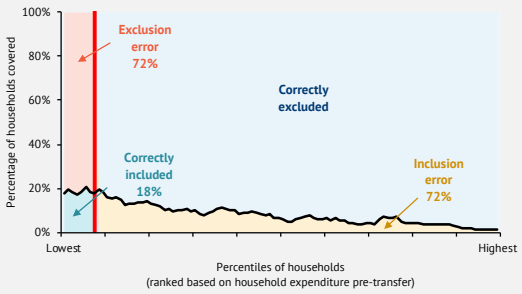


Source: own calculations using the PNAD 2017.

Uzbekistan has the worst performing means-test although only one of its three schemes was above the trend line in Figures 8 and 9, indicating worse than average performance. It may be that it performs less well than other means-tests due to its use of community volunteers during registration rather than professional public servants. Nonetheless, the performance of Uzbekistan's means-test is not too different to a number of well-known proxy means-tests. Further, Kidd et al (2019a) have compared Uzbekistan's current means-test with a theoretical proxy means-test and found that proxy means testing would not bring about any improvement despite costing at least $42 million per year to implement.

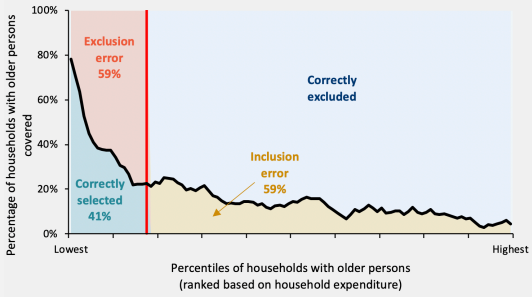
Figure 13: Targeting effectiveness of social protection schemes using means testing

a) Albania - *Ndihme Ekonomike*



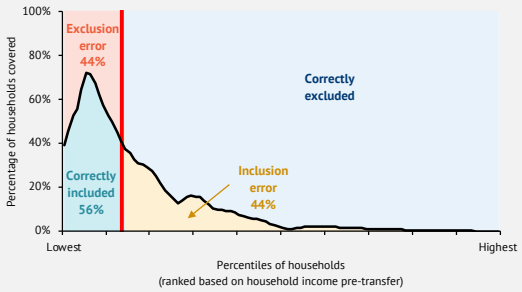
- ***Type of programme:*** Poor relief
- ***Eligibility***: Families living in poverty
- ***Coverage:*** 8%
- ***Survey***: LSMS 2012

b) Bangladesh – Old Age Pension



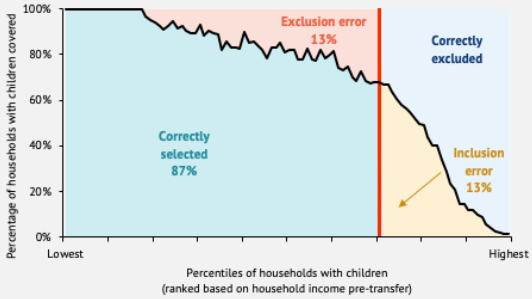
- ***Type of programme***: Old Age Pension
- ***Eligibility***: Women aged 62 years and above and men aged 65 years and above, with an annual income below BDT 3,000
- Coverage: 18%
- ***Survey***: HIES 2016

c) Brazil - *Bolsa Família*



- ***Type of programme***: Poor relief Conditional Cash Transfer
- ***Eligibility***: Families living in poverty
- Coverage: 14%
- ***Survey***: PNAD 2017

d) South Africa - Child Support Grant

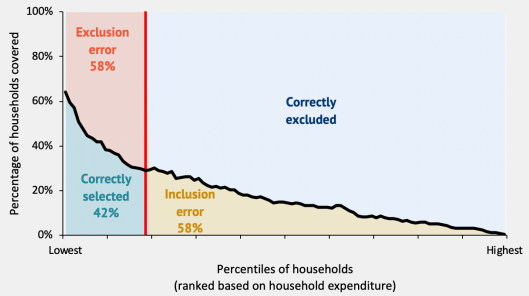


- ***Type of programme:*** Child benefit
- ***Eligibility***: Children in low income families
- ***Coverage***: 71%
- ***Survey***: GHS 2017

e) South Africa - Old Age Grant

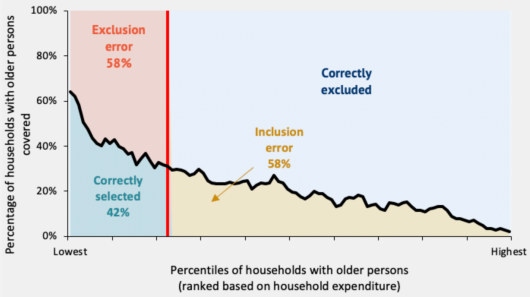
- ***Type of programme***: Old Age Pension
- ***Eligibility***: Adults aged 60 years and over with low incomes and/or assets valued below a specified threshold
- ***Coverage***: 84%
- ***Survey***: GHS 2017

f) Sri Lanka – *Samurdhi*



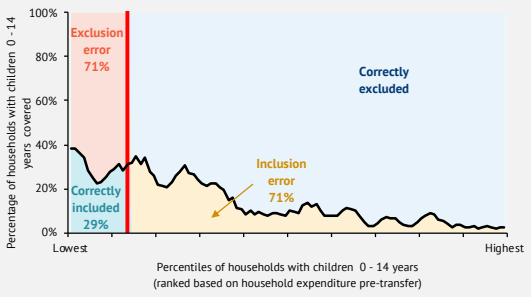
- ***Type of programme:*** Poor relief
- ***Eligibility***: Households living in poverty
- ***Coverage***: 19%
- ***Survey***: HIES 2016

g) Sri Lanka – Senior Citizens' Allowance



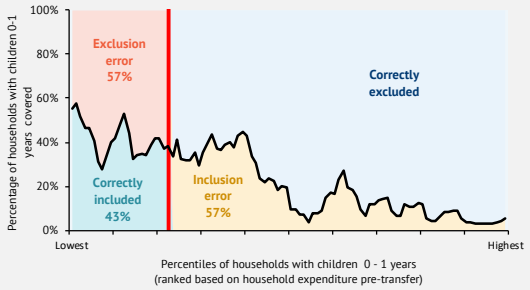
- ***Type of programme:*** Old Age Pension
- ***Eligibility***: Households with adults aged 70 years and above, living in poverty
- ***Coverage***: 23%
- ***Survey:*** HIES 2016

h) Uzbekistan - Family and Childcare Allowances



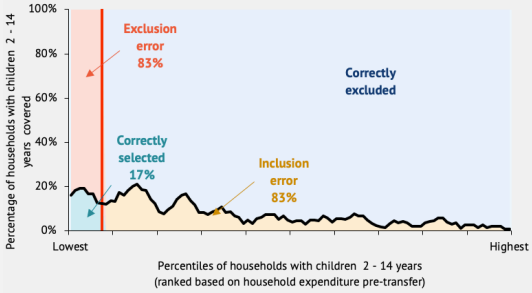
- ***Type of programme:*** Poor relief
- ***Eligibility***: Households with children aged between 0 and 14 years living in poverty
- ***Coverage***: 14%
- ***Survey:*** L2CU 2018

i) Uzbekistan - Childcare Allowance



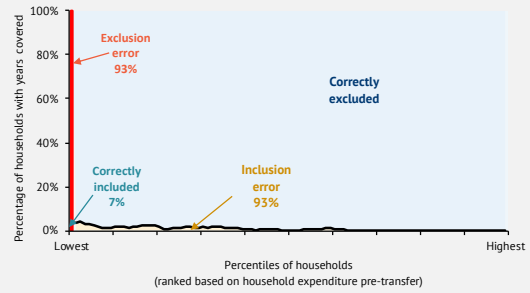
- ***Type of programme***: Poor relief
- ***Eligibility***: Households with children aged between 0 and 1 year living in poverty
- ***Coverage***: 23%
- ***Survey:*** L2CU 2018

j) Uzbekistan - Family Allowance



- ***Type of programme:*** Poor relief
- ***Eligibility***: Households with children aged between 2 and 14 years living in poverty
- ***Coverage***: 8%
- ***Survey:*** L2CU 2018

k) Uzbekistan – Low-Income Allowance



- ***Type of programme:*** Poor relief
- ***Eligibility***: Households living in poverty
- ***Coverage***: 1%
- ***Survey:*** L2CU 2018

Source: own calculations using the described national household surveys. Note: see Annex 2 for a detailed description of the methodology.

5.2.2 Proxy means testing

There were 19 schemes and registries using proxy means testing included in the research. Some of the schemes were iconic examples of proxy means-tests, such as Mexico's *Prospera* scheme, the Philippines' *Pantawid* (4Ps) programme, Pakistan's Benazir Income Support Programme (BISP), the Unified Database in Indonesia – which has been used for a number of schemes in the country – and Ghana's Livelihood Empowerment against Poverty (LEAP) programme. Unfortunately, few examples of proxy means-tests in Africa could be examined due to the lack of available data and the small size of many programmes.

Most of the schemes examined employ a typical World Bank style proxy means-test, following the methodology described in Section 2.2.2. However, India has developed its own form of proxy means-test – used in its Below Poverty Line registry – which is also included in this section. At least one scheme in the sample – Kenya's Hunger Safety Net Programme – used a combination of a proxy means-test and community-based targeting: communities selected an initial group that they believed were the poorest and the proxy means-test was subsequently applied to this group, although the proxy means-test survey itself was undertaken across the entire population of the area covered by the programme (although, of course, an unknown proportion of households were not found during the survey).

A summary of the programmes examined, alongside their coverage and errors, is set out in Table 4. The results for individual schemes – with graphs – can be found in Figure 19. The targeting errors for the programmes – when measured against coverage – vary between 29 per cent for Uruguay's *Asignaciones Familiares* scheme and 96 per cent for Guatemala's *Mi Bono Seguro* programme. Indeed, some programmes – such as *Mi Bono Seguro* and Kenya's Hunger Safety Net Programme (HSNP) – are little better than random selection.[31] In other words, these schemes could have used a lottery and the result would not have been much different.

[31] Silva-Leander and Merttens (2016) came to a similar conclusion regarding the Hunger Safety Net Programme.

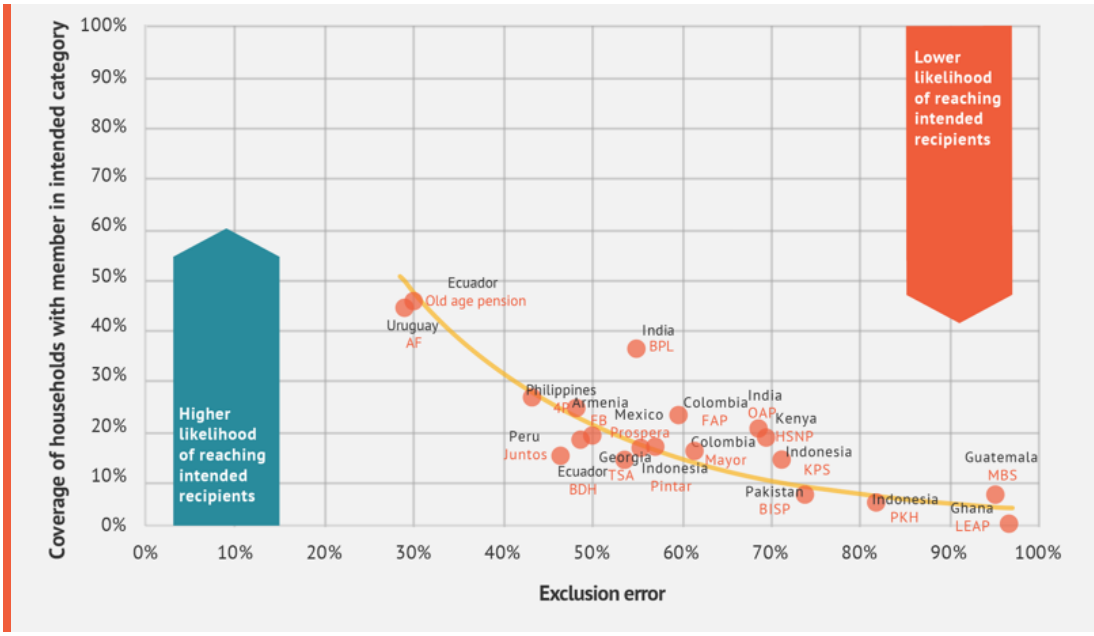
Table 4: Summary of the results from programmes using proxy means-tests

Country	Scheme	Coverage (as percentage of intended category)	Targeting Error	
			Exclusion errors with respect to intended recipients (percentage)	Exclusion of those in bottom 20% (percentage)
Armenia	Family Benefits	19	49	50
Colombia	*Familias en Acción*	23	59	60
Colombia	*Programa Colombia Mayor*	19	61	61
Ecuador	*Bono de Desarrollo Humano*	18	48	50
Ecuador	Social Pension	46	30	19
Georgia	Targeted Social Assistance	15	53	58
Ghana	Livelihood Empowerment Against Poverty	1	95	97
Guatemala	*Mi Bono Seguro*	7	96	95
India	Indira Gandhi National Old Age Pension Scheme	21	68	68
India	Below Poverty Line	36	54	51
Indonesia	*Program Keluarga Harapan*	7	82	85
Indonesia	*Kartu Perlindungan Sosial*	14	71	73
Indonesia	*Pintar*	18	56	66
Kenya	Hunger Safety Net Programme	20	69	69
Mexico	*Prospera*	18	54	56
Pakistan	Benazir Income Support Programme	8	73	79
Peru	*Juntos*	16	46	50
Philippines	*Pantawid Pamilyang Pilipino* Program	23	48	46
Uruguay	*Asignaciones Familiares*	45	29	17

Source: own calculations using the national household surveys described in Table 1. Note: see Annex 2 for a detailed description of the methodology.

However, as observed earlier across all programmes, there is a negative correlation between coverage and targeting effectiveness (in this case the correlation coefficient was -0.80). As Figure 14 shows, the higher the coverage, the lower the error. Among schemes with low coverage – in other words, 10 per cent of the intended category or less – errors become very high: Pakistan's BISP has an exclusion error of 73 per cent, Indonesia's PKH excludes 82 per cent of its intended recipients, while the exclusion from Guatemala's and Ghana's poor relief schemes is around 95 per cent (in other words, only around 1 in 20 of the intended recipients can access the schemes).

Figure 14: Relationship between coverage and exclusion error in programmes using proxy means-tests



Source: own calculations using the national household surveys described in Table 1. Note: see Annex 2 for a detailed description of the methodology.

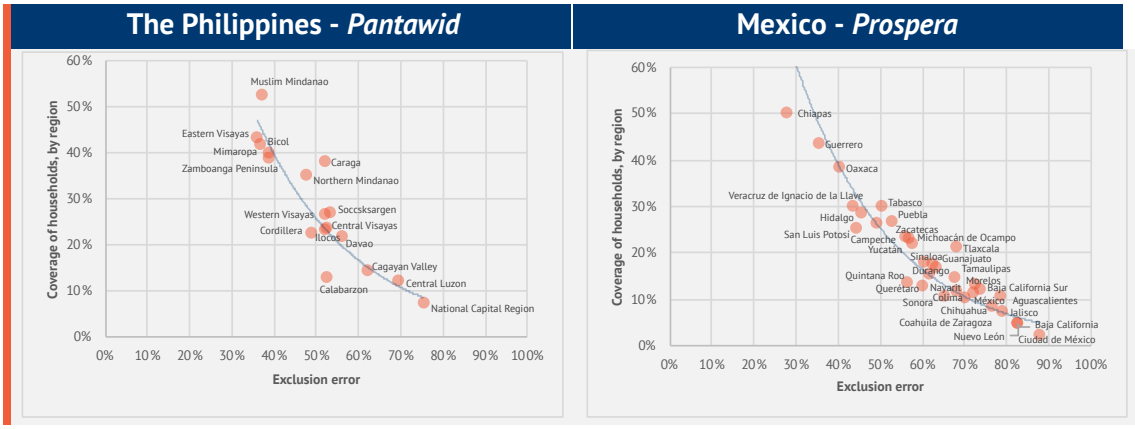
Figure 14 also demonstrates which proxy means-tests perform better than the norm and which are below par. Those above the trend line are performing worse than average and those below the line are performing better than average. Peru's *Juntos* scheme appears to be performing best – as it is furthest from the trend line among those with above average performance – but still has an exclusion error of 46 per cent. India's Below Poverty Line (BPL) Registry is particularly ineffective and, in both graphs, is well above the trend line, as is India's Old Age Pension which uses the BPL Registry. However, the weak performance of the BPL Registry has probably been exacerbated by the reported corruption linked to the BPL Registry.[32] Once India's schemes are discounted, Colombia and Kenya appear to have the worst performing proxy means-test, given that they are a long way above the trend line.

The importance of coverage in determining targeting effectiveness can also be observed when examining how well schemes perform within the different regions of a country. Figure 15 shows the relationship between coverage and exclusion errors within the Philippines' *Pantawid* and Mexico's *Prospera* programmes. In both, there is, as expected, a strong correlation between higher coverage and lower errors (a correlation coefficient of -0.89 in the case of the *Pantawid* programme and -0.94 for *Prospera*). Exclusion errors

[32] Niehaus et al (2013); Kidd (2017c).

reach up to 75 per cent with the *Pantawid* programme and almost 90 per cent with *Prospera*. This indicates that, if both schemes had lower coverage, their errors would likely be higher. Further, since many proxy means-tests include a geographic proxy, it is likely that much of the – limited – targeting effectiveness of proxy means-tests depends on the geographic proxy rather than the assessment of specific household factors (see Box 8).

Figure 15: Relationship between coverage and exclusion errors across regions in the Philippines *Pantawid* and Mexico's *Prospera* programmes



Source: own calculation using the APIS 2014 (Philippines) and ENIGH 2016 (Mexico).

Box 8: Geographic proxies in proxy means-tests

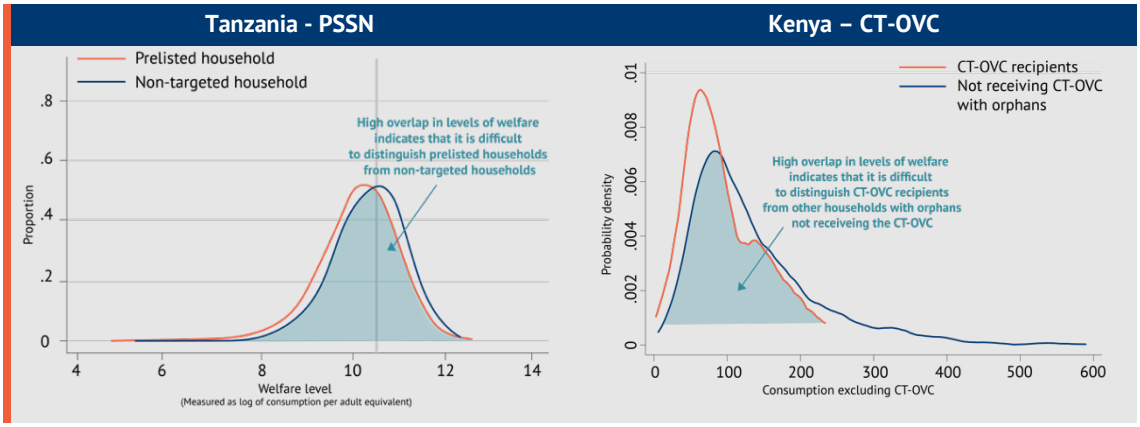
In many PMTs, it is common to include a geographic variable to increase their predictive power. This reflects the fact that some areas of a country are better-off than others and, if a household lives in a better-off area, it is more likely, on average, to have a higher income than a household living in a poorer area. Yet, the inclusion of a geographic variable means that households are not assessed on their own merits, but on the well-being of others living in their region. So, if two households are exactly the same in all respects apart from their area of residence, the household in the poorer area of the country will have a greater likelihood of being selected by the PMT than the household in the better-off region. While this may decrease exclusion errors, it is clearly unfair to those living in extreme poverty in better-off areas.

As indicated earlier, some social protection schemes – in particular in Africa – combine community-based targeting with proxy means-tests, believing that this will generate greater accuracy. The only example that we were able to study was Kenya's Hunger Safety Net Programme which, as indicated above, performs little better than a lottery. However, the World Bank (2016) undertook analysis of Tanzania's Productive Social Safety Net (PSSN) programme and found a similar result. Figure 16 reproduces a graph from the World Bank's report which compares the consumption of households pre-selected by the community and those not selected. The X axis shows the consumption from poorest to richest (expressed in log form) while the Y axis gives the proportion of households with each level of consumption. Those identified by communities as potentially eligible for the PSSN programme are in red while those rejected by the communities are in blue. Given

that only 3 per cent of those households pre-selected by the community were excluded by the PMT, the consumption pattern of the actual recipients following the PMT will be very similar to the pattern in Figure 16. The large overlap between the two curves indicates that there is little difference in the consumption of selected and non-selected households. Similar analysis has been undertaken of Kenya's Cash Transfer for Orphans and Vulnerable Children (CT-OVC) programme, which also uses a combination of community-based targeting and a proxy means test: as in Tanzania, Figure 16 shows a significant overlap between recipients and non-recipients, indicating a similarly poor targeting outcome.

The proxy means-test forms the basis of many of the Social Registries currently being developed and implemented in low- and middle-income countries.[33] Social Registries are an attempt to rank households in a country from poorest to richest based – usually – on a PMT survey. The logic behind a Social Registry – which is very different from a Single Registry (see Box 9) – is that the PMT survey can be used to select recipients of multiple poverty-targeted programmes, rather than just one. The PMTs for most of the schemes in our research provide the data for national Social Registries.

Figure 16: Effectiveness of the combination of targeting methods in Tanzania's Productive Social Safety Net (PSSN) programme and Kenya's Cash Transfer for Orphans and Vulnerable Children (CT-OVC)



Source: adapted from World Bank (2016) and Republic of Kenya (2019).

Our research indicates that all Social Registries using PMTs are failing badly, given their high levels of inaccuracy. If the errors found in the social protection programmes assessed in the research are replicated across other social programmes using the same Social

[33] The *Cadastro Unico* in Brazil is one of the few examples of a Social Registry that does not use a proxy means-test. Instead, it uses a means-test which is the basis of selection for *Bolsa Familia*. However, Brazil has a separate database – known as as *Cadastro Nacional de Informações Sociais* (CNIS) – which is much more similar to a Single Registry

Registry, it is likely that the majority of households living in extreme poverty across a range of countries are being systematically excluded from multiple schemes.[34]

The results from our research contradict the claim by the World Bank that the proxy means-test 'can accurately and cost effectively target the chronic poor.'[35] Instead, proxy means testing clearly comes nowhere near being an accurate targeting mechanism. Across all schemes studied, the average error was 60 per cent while a number of schemes exhibited errors above 90 per cent. If policymakers are serious about reaching the poorest members of society with social protection, then the evidence indicates that they must discard the proxy means-test – and Social Registries – as an option.

There is a range of reasons explaining the weak targeting effectiveness of proxy means-tests, which are summarized in Kidd and Wylde (2011) and Kidd et al (2017). These include design errors, challenges with implementing surveys and infrequent re-targeting. Each is discussed below.

Box 9: Distinguishing Single Registries from Social Registries

Single Registries and Social Registries are very different concepts. As Chirchir and Farooq (2016) point out, a Single Registry is essentially a warehouse of information on a range of social protection programmes, which can also be linked to other national databases (such as the tax or civic registration databases). A key function of Single Registries is that they facilitate the monitoring of national systems of social protection. A good example of a Single Registry can be found in Kenya.

In contrast, Social Registries collect information on households nationally which can be used to predict their well-being, usually through an algorithm-based PMT. As indicated in this paper, PMTs – and hence the Social Registries based on them – are highly inaccurate and tend to exclude the majority of people living in poverty from social programmes. Interestingly, recent legislation in the European Union – the General Data Protection Regulation (GDPR) – effectively bans the use of algorithms alone for selection purposes. It states, in Article 22: 'The data subject shall have the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her or similarly significantly affects him or her.' Nonetheless, European countries – and international institutions financed by European countries – continue to promote and fund the use of PMTs to make automated decisions among non-Europeans despite being banned from doing so among their own citizens.

The PMT is different to many other poverty targeting mechanisms in that, even before it is implemented, it already incorporates very significant inaccuracies – or design errors – which are derived from the way in which it is developed. The reason is a relatively weak correlation between the multiple proxies employed in the algorithm and income (or consumption). When the proxies are identified in household surveys, the R-squared – which measure the 'goodness-of-fit' or how much of the variance in consumption or income can be explained by the model– is usually between 40 and 60 per cent, whereas

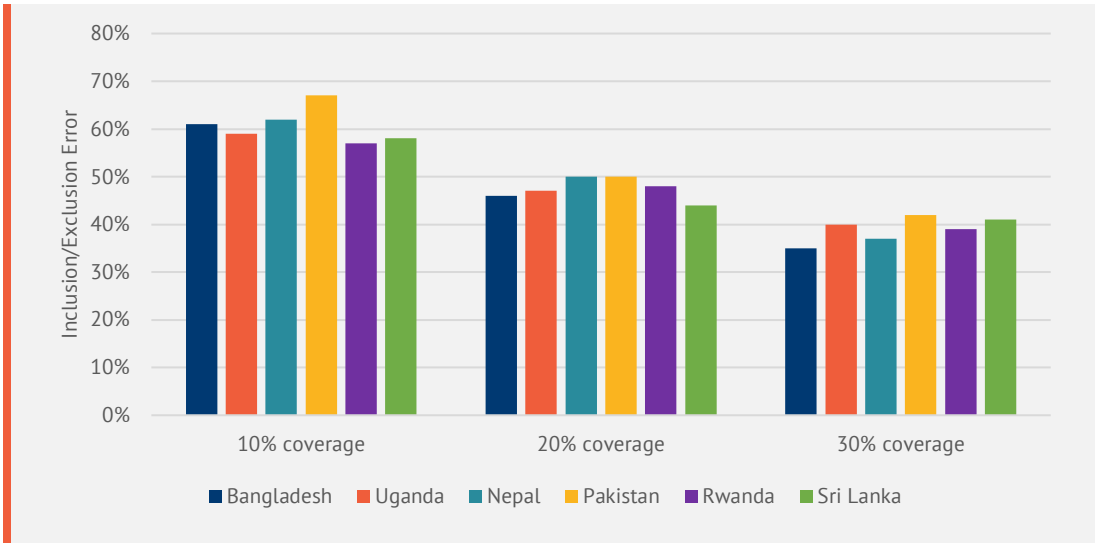
[34] For a further discussion, see Kidd (2017a)

[35] Leite (2014). See also Del Ninno and Mills (2015) who make the same claim.

100 per cent indicates a perfect correlation.[36] In other words, around half of the variation in consumption or income between households remains unexplained.

Figure 17 indicates the design errors found across a number of PMTs. The lower the coverage, the higher the design error. Indeed, when 10 per cent of the population is targeted, around 60 per cent of the poorest 10 per cent are excluded by design. The design error decreases to around 50 per cent when 20 per cent of the population is excluded. Occasionally, though, design errors can be much higher: in Kenya, the World Bank designed a PMT with a design error of over 70 per cent when targeted at the poorest 10 per cent of the population; and, in Zambia, Oxford Policy Management designed a PMT that had a design error of 75 per cent when targeted at the poorest 10 per cent.[37] However, both of these proxy means-tests were developed using principal component analysis which does not attempt to directly predict consumption or income.

Figure 17: Design errors from the proxy means-test at different levels of coverage across six countries



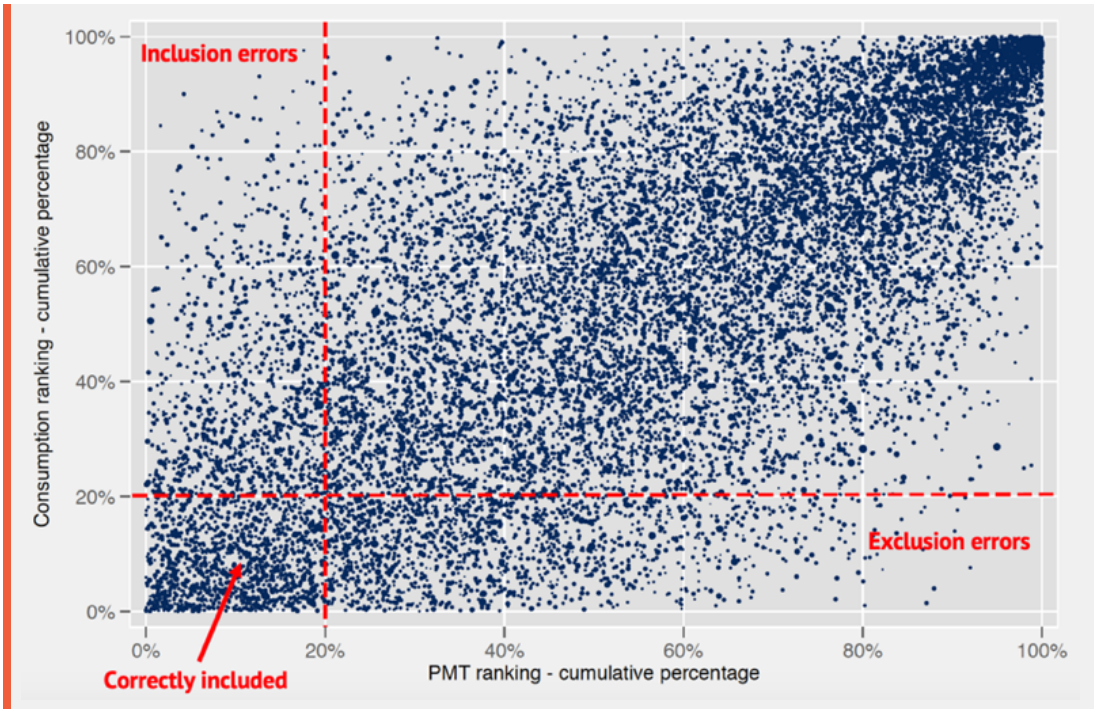
Source: Kidd et al (2010), Kidd and Wylde (2011), Kidd et al (2011) and Kidd and Bailey-Athias (2016).

In fact, the PMT mechanism is relatively arbitrary in its targeting, which explains why many people subjected to it regard it as a lottery.[38] Figure 18 shows a scatter graph of the design errors in a PMT for Uganda, an example of a relatively well-performing PMT with

[36] While a R-squared of 0.4 to 0.6 would usually be regarded as a good result in statistics, it is a weak result when the impacts of the errors can cause significant harm to the well-being of tens of millions of people.
[37] Abu-el-Haj (2015); Kidd et al (2017); Beazley and Carraro (2013). In both these cases, the PMT was developed without using consumption or income. Indeed, in Kenya, the PMT was developed using the national census (Villa 2016).
[38] Kidd and Wylde (2011) and Kidd et al (2017c).

an R-squared of 0.5.[39] Each household in the Ugandan dataset is mapped – using a blue dot to identify it – according to its ranking in terms of its consumption predicted by the PMT (the X axis) alongside its actual consumption as recorded in the national household survey (the Y axis).[40] If the PMT could perfectly predict a household's level of consumption, all households would be lined up along a diagonal from the bottom left corner to the top right corner. The reality is very different, with households widely scattered across the graph. Those to the left of the vertical red line would be predicted by the PMT to be in the poorest 20 per cent of the population and would be included in the programme. However, in reality, the poorest 20 per cent of households are those under the horizontal red line. Only 51 per cent of households in the poorest 20 per cent are correctly targeted.

Figure 18: Scattergraph indicating the design errors of a PMT in Uganda



Source: own calculations using the Uganda National Household Survey 2016-17.

[39] The dataset used in the analysis is from the Uganda National Household Survey (2016/17).

[40] Larger blue dots indicate multiple households.

Additional errors are incorporated in PMTs once they are implemented. Data collection is often of poor quality: for example, in Indonesia, in 2011, it was found that, on average, the data in almost 15 per cent of cells had been inaccurately entered.[41] It is also relatively easy for those interviewed to give incorrect answers: once households have experience of the PMT, they know how to adapt their answers to make themselves look poorer than they are.[42] Further errors are generated if re-targeting is undertaken infrequently, which often happens due to the high cost of PMTs (see Section 2.2.2). Pakistan, for example, has not undertaken a PMT survey since 2009; the Philippines has also not re-done its PMT since 2009;[43] in Indonesia, there was a four-year gap between surveys in 2011 and 2015 and it has not yet been repeated; while, in some areas of Mexico, registration for the *Oportunidades* – now *Prospera* – programme had not been repeated for more than 10 years.[44]

[41] SMERU (2011).

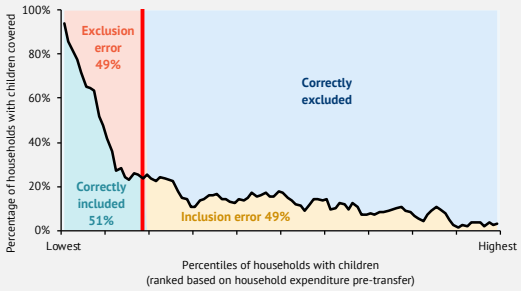
[42] For further information on errors during implementation, see Kidd and Wylde (2011) and Kidd et al (2017).

[43] We understand that the Pantawid programme has re-designed the algorithm for its PMT but a new survey has not yet been undertaken.

[44] Zoletto (2011). Villa and Niño-Zarazúa (2018) claim that re-targeting is done every three years, but it is unclear whether they are stating official policy or what has been happening in practice in recent years.

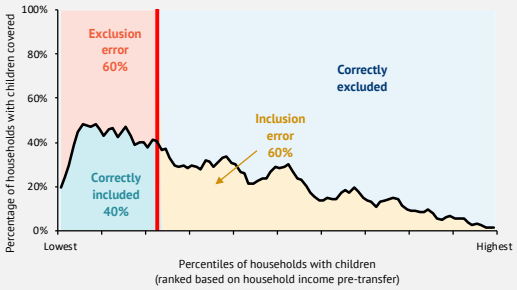
Figure 19: Targeting effectiveness across schemes using proxy means testing

a) Armenia - Family Benefits



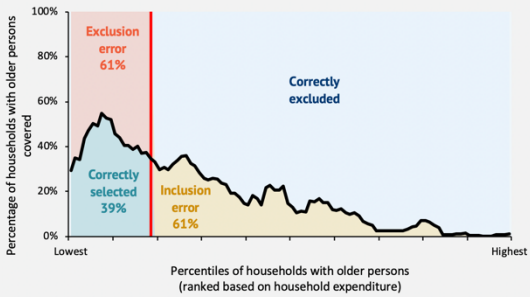
- ***Type of programme:*** Poor relief
- ***Eligibility***: Families with children living in poverty
- ***Coverage:*** 19%
- ***Survey*:** HILCS 2016

b) Colombia - *Familias en Acción*



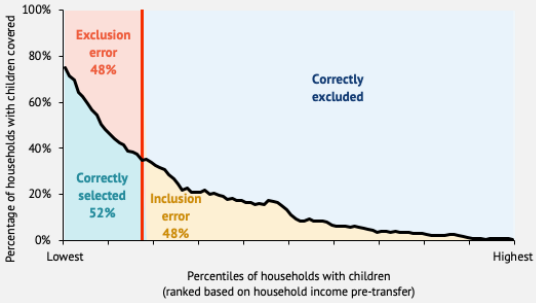
- ***Type of programme***: Poor relief Conditional Cash Transfer
- ***Eligibility***: Households with children living in poverty
- ***Coverage***: 23%
- ***Survey*:** ECV 2017

c) Colombia – *Programa Colombia Mayor*



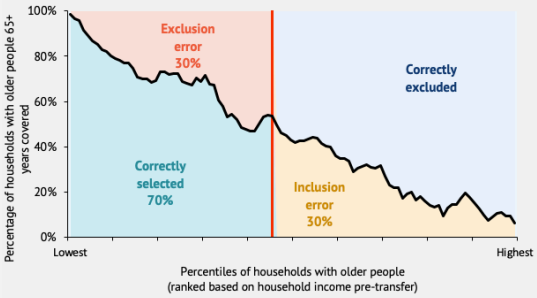
- ***Type of programme***: Old Age Pension
- ***Eligibility***: Women aged 54 years and over and men aged 59 years and over, living in poverty
- ***Coverage***: 19%
- ***Survey*:** ECV 2017

d) Ecuador - *Bono de Desarollo Humano*



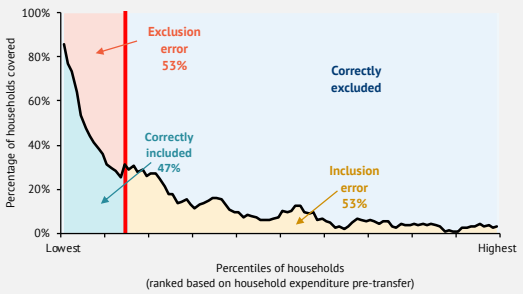
- ***Type of programme***: Poor relief Conditional Cash Transfer
- ***Eligibility***: Households with children under 16 years living in poverty
- ***Coverage***: 18%
- ***Survey*:** ENCV 2013

e) Ecuador - Social Pension



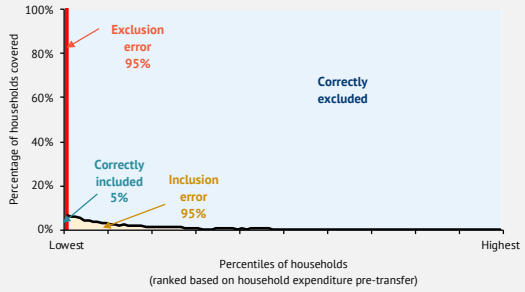
- ***Type of programme***: Old Age Pension
- ***Eligibility***: Adults aged 65 years and over living in poverty
- ***Coverage***: 46%
- ***Survey*:** ENCV 2013

f) Georgia - Targeted Social Assistance



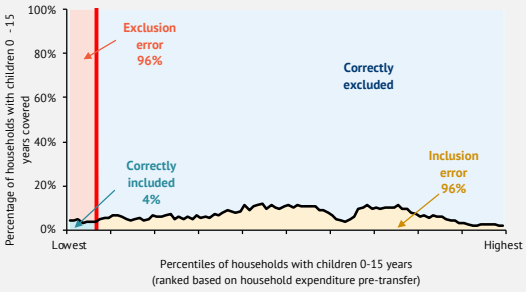
- ***Type of programme:*** Poor relief
- ***Eligibility***: Families living in poverty
- ***Coverage***: 15%
- ***Survey*:** WMS 2015

g) Ghana - Livelihood Empowerment Against Poverty



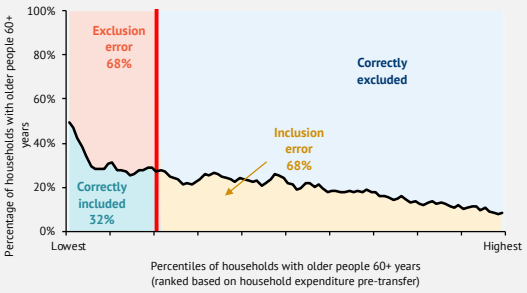
- ***Type of programme***: Poor relief
- ***Eligibility***: Households living in poverty
- ***Coverage:*** 1%
- ***Survey***: GLSS7 2017

h) Guatemala - *Mi Bono Seguro*



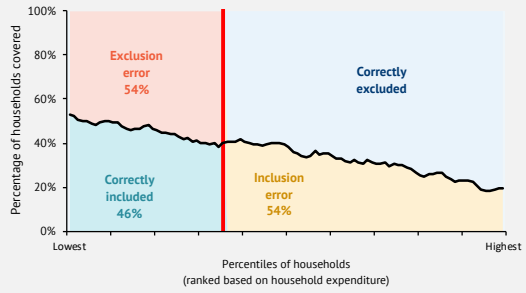
- ***Type of programme***: Poor relief Conditional Cash Transfer
- ***Eligibility***: Families living in poverty with children aged 15 years and under
- ***Coverage:*** 7%
- ***Survey***: ENCOVI 2014

i) India - Indira Gandhi National Old Age Pension Scheme



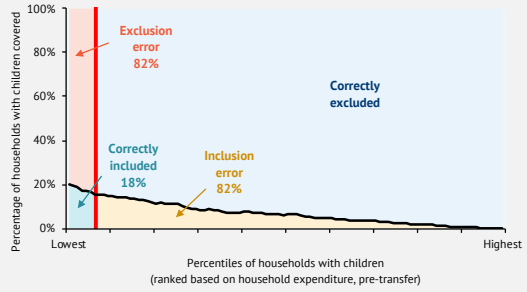
- ***Type of programme***: Old Age Pension
- ***Eligibility***: Adults aged 60 years and above living in poverty
- ***Coverage***: 21%
- ***Survey***: IHDS 2012

j) India - Below Poverty Line



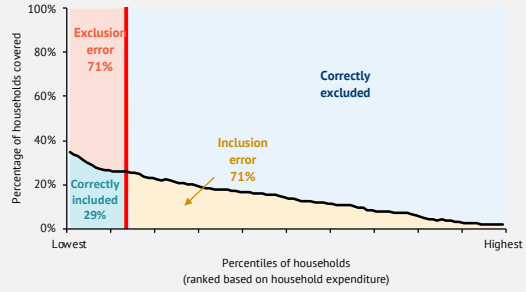
- ***Type of programme:*** Registry
- ***Eligibility***: Families living in poverty
- ***Coverage***: 36%
- ***Survey***: IDHS 2012

k) Indonesia - *Program Keluarga Harapan*



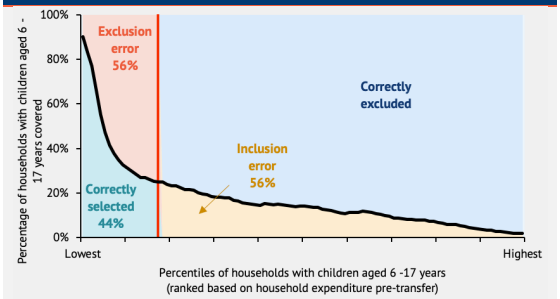
- ***Type of programme***: Poor relief Conditional Cash Transfer
- ***Eligibility***: Families with children and/or pregnant or lactating women living in poverty
- ***Coverage***: 7%
- ***Survey***: SUSENAS 2017

l) Indonesia - *Kartu Perlindungan Sosial*



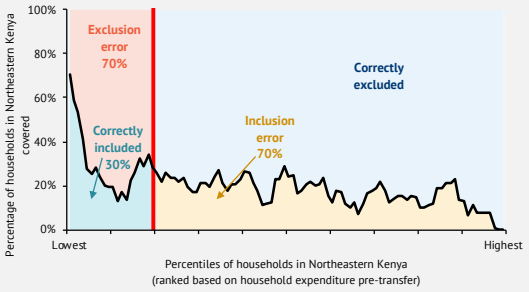
- ***Type of programme:*** Registry
- ***Eligibility***: Families living in poverty
- ***Coverage***: 14%
- ***Survey***: SUSENAS 2017

m) Indonesia - *Pintar*



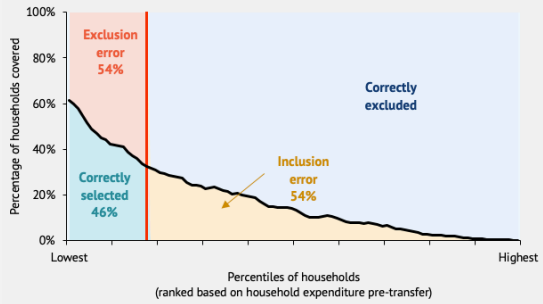
- ***Type of programme***: School stipend scheme
- ***Eligibility***: Families with children aged 6 to 17 years living in poverty
- ***Coverage***: 18%
- ***Survey***: SUSENAS 2017

n) Kenya - Hunger Safety Net Programme



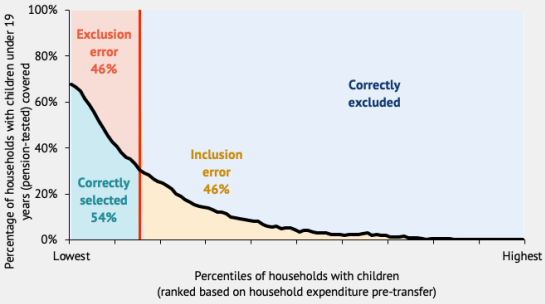
- ***Type of programme***: Unconditional Cash Transfer
- ***Eligibility***: Households in Northeastern Kenya living in poverty
- ***Coverage***: 20%
- ***Survey***: KIHBS 2016

o) Mexico - *Prospera*



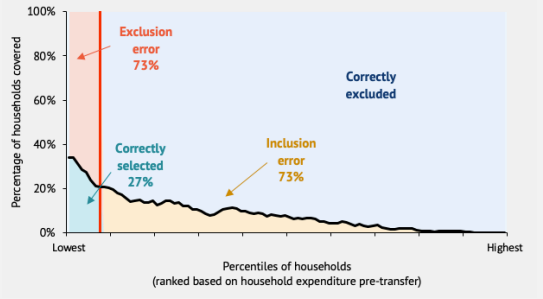
- ***Type of programme***: Poor relief Conditional Cash Transfer
- ***Eligibility***: Households living in poverty
- ***Coverage***: 18%
- ***Survey***: ENIGH 2016

p) Peru - *Juntos*



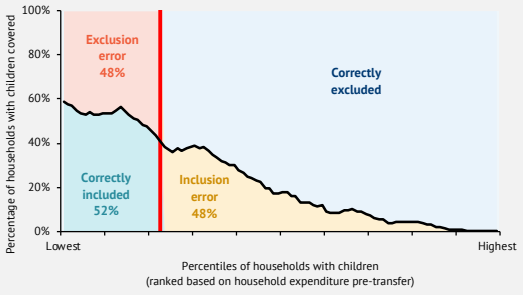
- ***Type of programme***: Poor relief Conditional Cash Transfer
- ***Eligibility***: Households with children aged 19 years and under and/or pregnant and breastfeeding women living in poverty
- ***Coverage***: 16%
- ***Survey***: ENAHO 2017

q) Pakistan - Benazir Income Support Programme



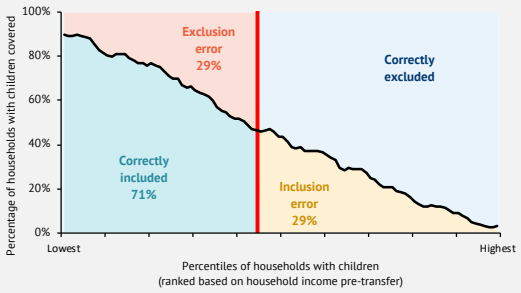
- ***Type of programme***: Poor relief
- ***Eligibility***: Families living in poverty
- ***Coverage***: 8%
- ***Survey***: HIES 2016

r) Philippines - *Pantawid Pamilyang Pilipino Program*



- ***Type of programme***: Poor relief Conditional Cash Transfer
- ***Eligibility***: Households with children aged 18 years and under and/or pregnant women living in extreme poverty
- ***Coverage***: 23%
- ***Survey***: APIS 2014

s) Uruguay - *Asignaciones Familiares*



- ***Type of programme***: Poor relief Conditional Cash Transfer
- ***Eligibility***: Families with children aged 17 years and under and/or people with disabilities living in poverty
- ***Coverage***: 45%
- ***Survey:*** ECH 2016

Source: own calculations using the national household surveys described in Table 1. Note: see Annex 2 for a detailed description of the methodology.

5.2.3 Community-based targeting

Our research examined national-level programmes and registries using community-based targeting across three countries: Ethiopia, Rwanda and Vietnam. A summary of the results can be found in Table 5 and targeting effectiveness graphs for individual schemes can be found in Figure 20.

Table 5: Summary of the results from programmes using community-based targeting

Country	Scheme	Coverage (as percentage of intended category)	Targeting Error	
			Exclusion errors with respect to intended recipients (percentage)	Exclusion of those in bottom 20% (percentage)
Ethiopia	Productive Safety Net Programme (combined)	12	81	83
Ethiopia	Productive Safety Net Programme (direct support)	8	80	86
Ethiopia	Productive Safety Net Programme (public works)	9	87	88
Rwanda	*Vision 2020 Umurenge* Programme (combined)	3	95	96
Rwanda	*Vision 2020 Umurenge* Programme (public works)	2	97	97
Rwanda	*Vision 2020 Umurenge* Programme (direct support)	10	90	89
Rwanda	*Ubudehe* (groups 1 and 2)	30	53	49
Vietnam	Poor List	11	49	63

Source: own calculations using the national household surveys described in Table 1. Note: see Annex 2 for a detailed description of the methodology.

Vietnam's Poor List – with selection undertaken by community leaders – stands out as a relatively effective registry. It attempts to identify the poorest households in Vietnam and, in 2016, 10.6 per cent were assessed as fulfilling the criteria. The exclusion error among identified households was 49 per cent, making it one of the best performing schemes.

The two African examples of community-based targeting in our research were from Ethiopia and Rwanda. Ethiopia's Productive Safety Net Programme (PSNP) is financed mainly by international donors and reaches 12 per cent of households in the regions where it operates. Its exclusion error against its intended recipients is 81 per cent. The scheme has two components: an unconditional cash transfer called Direct Support for households 'without labour capacity' – in other words those without a non-disabled working age member – and a workfare programme. When assessed against their intended recipients, targeting on the Direct Support component has lower errors than the workfare component: 80 per cent against 87 per cent.[45] In reality, the PSNP scheme appears to perform little better than random selection.[46] As discussed earlier, this means that the PSNP may as well use a simple form of lottery as it would deliver almost the same result.

Rwanda's *Ubudehe* mechanism was developed in 2002 as a means of assessing well-being across the national population. Each year, communities ranked each household across six well-being categories and the results were used to monitor progress across the country. However, *Ubudehe* gradually became adopted as the targeting mechanism for Rwanda's *Vision 2020 Umurenge Programme* (VUP) and the *Mutuelle de Sante* health support programme: in effect, it became a form of registry. Those in the two lowest *Ubudehe* categories – corresponding to 30.1 per cent of the population in 2014 – were eligible for the schemes. Our research found that the exclusion error, when identifying the two lowest categories (1 and 2), was 53 per cent, a result on a par with many good proxy means-tests.

Rwanda's VUP scheme is – as with Ethiopia's PSNP scheme – divided into two components: Direct Support for those households that were 'labour constrained' and workfare for others. While the VUP used *Ubudehe* for selecting its recipients, coverage has been much lower than the total number of households in Categories 1 and 2. This probably contributed to errors being much higher in VUP: for the whole scheme, which covered 3 per cent of its intended category in 2014, the errors were 95 per cent. For Direct Support, 10 per cent of labour constrained households nationally were reached, but exclusion errors were 90 per cent.[47] Across the workfare component, which reached 2 per

[45] The 2015 Ethiopia Socioeconomic Survey (ESS) includes the Washington Group Set of questions and so, as a result, we could construct a population of households that fit the criterion "without labour capacity."

[46] The effectiveness of Ethiopia's PSNP scheme in targeting people with disabilities can be found in Kidd et al (2019b).

[47] The Integrated Household Living Conditions Survey (EICV) of 2014 in Rwanda included a question on disability and we used this to construct the population of labour-constrained households.

cent of households with at least one non-disabled working age member, the error was 97 per cent. In other words, almost nobody within the target population at the time of the survey was accessing the programme.[48] As with Ethiopia's PSNP, Rwanda's VUP appears to perform little better than random selection. Rwanda has recently replaced its community-based targeting with a simple form of proxy means-test although, when first used, almost 40 per cent of households across the country appealed against their classification.[49]

The main argument put forward in favour of community-based targeting is that 'communities know best' when determining who are most in need. Yet, this view is based on a rather romantic and naïve conception of communities as homogenous and harmonious entities. In reality, most communities comprise many sub-groups – frequently overlapping – which are often in tension with each other. They are also often very unequal, with some community members experiencing social exclusion. This is particularly the case in larger communities that have been formed in recent decades as a result of population movements and migration.

There is a range of reasons for the inaccuracies in community-based targeting. When it works well, it is able to select the most destitute in the community – as these are often easy to identify – as long as they have not been socially excluded, but this group is normally a very small proportion of households. Across the rest of the community, decisions are more arbitrary, due to the relative similarity between most households which, combined with income dynamics, means that it is very difficult to differentiate between them. McCord (2017) explains how biases in community meetings 'may result from social inclusion/exclusion; social norms relating to, for example, wealth, ethnicity, religion or caste; the practicalities of participation by labour-constrained households; or the time or geographical location of the meeting, all of which can have impacts on which segments of the community have voice and hence the resulting targeting outcomes.'[50]

A further challenge with community-based targeting is that it is often based on a fixed quota for each community (such as the poorest 10 per cent). Yet, the well-being of communities can vary greatly across a country: the poorest 10 per cent in a relatively well-off community may have higher standards of living than the more affluent members of a poor community. In effect, quotas can lead to beneficiaries from poor communities being under-represented in national programmes while those from more affluent communities can be over-represented.[51]

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[48] The VUP workfare component is only given to households for a short period of time: no more than 60 days per year. In part, this probably explains the low coverage at the time of the survey.

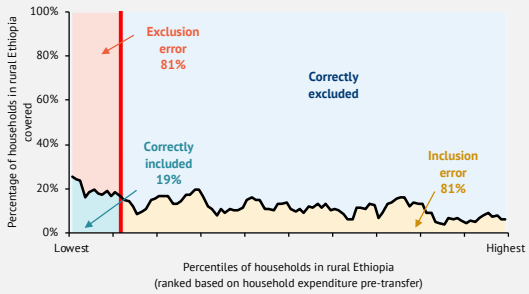
[49] LODA (2016).

[50] Cf. Isik-Dikmelik 2009; and, Kidd et al 2011.

[51] See Kidd and Bailey-Athias (2016) for further explanation.

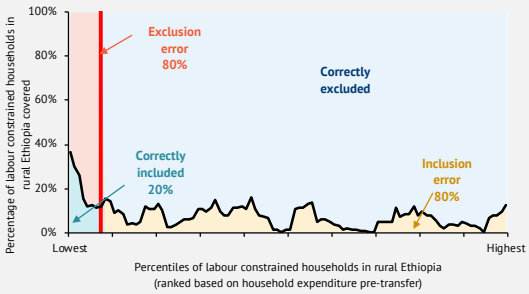
Figure 20: Targeting effectiveness of schemes using community-based targeting

a) Ethiopia - Productive Safety Net Programme



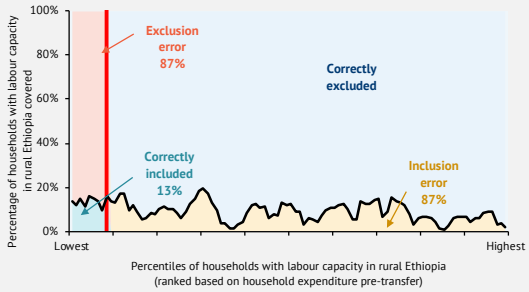
- ***Type of programme***: Poor relief and workfare
- ***Eligibility***: Chronically food insecure households in rural Ethiopia
- ***Coverage***: 12%
- ***Survey***: ESS 2015

b) Ethiopia - Productive Safety Net Programme (direct support)



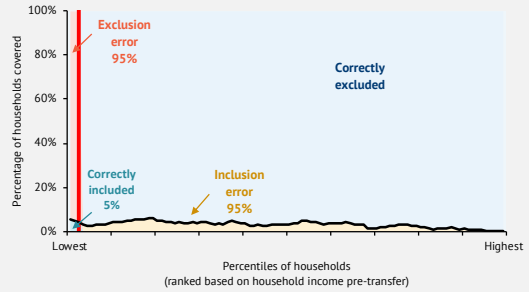
- ***Type of programme***: Poor relief
- ***Eligibility***: Chronically food insecure households in rural Ethiopia that are labour constrained
- ***Coverage***: 8%
- ***Survey***: ESS 2015

b) Ethiopia - Productive Safety Net Programme (public works)



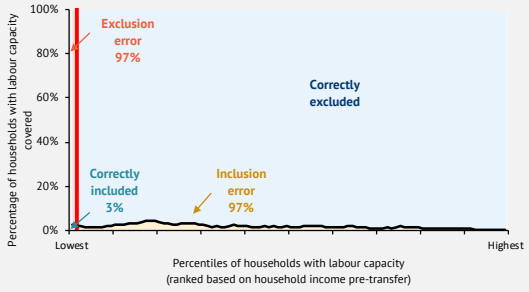
- ***Type of programme:*** Workfare
- ***Eligibility***: Chronically food insecure households with labour capacity in rural Ethiopia
- ***Coverage***: 9%
- ***Survey***: ESS 2015

b) Rwanda - *Vision 2020 Umurenge Programme*



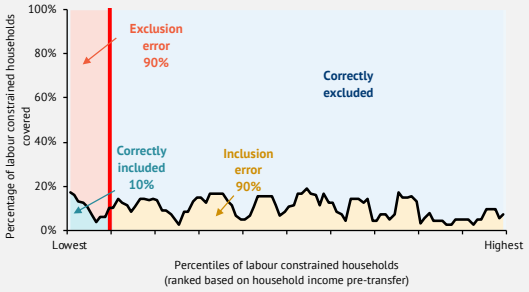
- ***Type of programme***: Workfare and poor relief
- ***Eligibility***: Households living in poverty
- ***Coverage***: 3%
- ***Survey***: EICV 2014

c) Rwanda - *Vision 2020 Umurenge Programme* (public works)

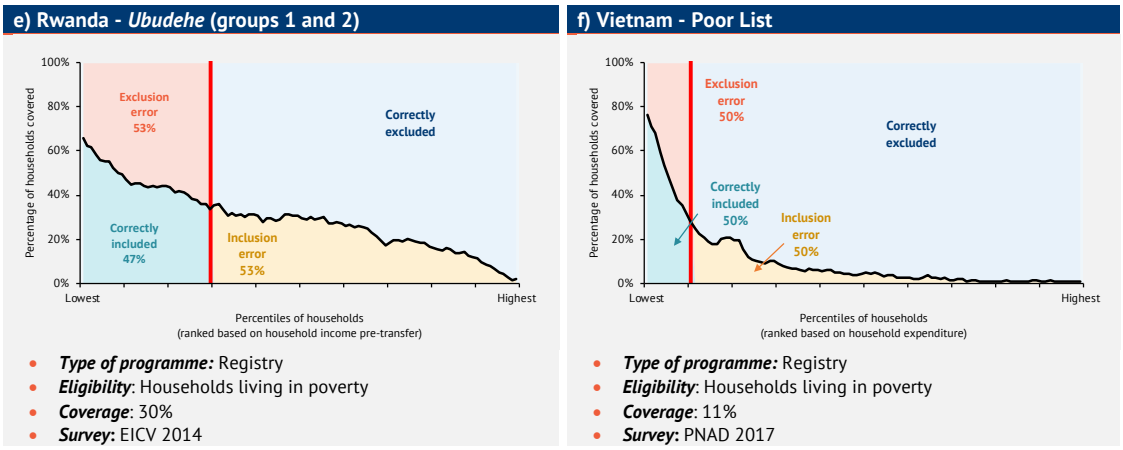


- ***Type of programme:*** Workfare
- ***Eligibility***: Households living in poverty with labour capacity
- ***Coverage***: 2%
- ***Survey***: EICV 2014

d) Rwanda - *Vision 2020 Umurenge Programme* (direct support)



- ***Type of programme***: Poor relief
- ***Eligibility***: Households living in poverty that are labour constrained
- ***Coverage***: 10%
- ***Survey***: VHLSS 2016



Source: own calculations using the national household surveys described in Table 1. Note: see Annex 2 for a detailed description of the methodology.

5.2.4 Self-targeting

The research examined only one scheme using self-targeting: India's Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) scheme, a workfare programme. All households in rural areas are, in theory, guaranteed up to 100 days employment per year on the scheme. Our research indicated that it reached 29 per cent of households in rural India in 2012. However, as Figure 22 shows, the distribution of recipients across the welfare distribution is relatively flat and, among the poorest 20 per cent of the intended category, 61 per cent were not accessing the programme at the time of the survey.

Table 6: Targeting errors among a programme using self-targeting

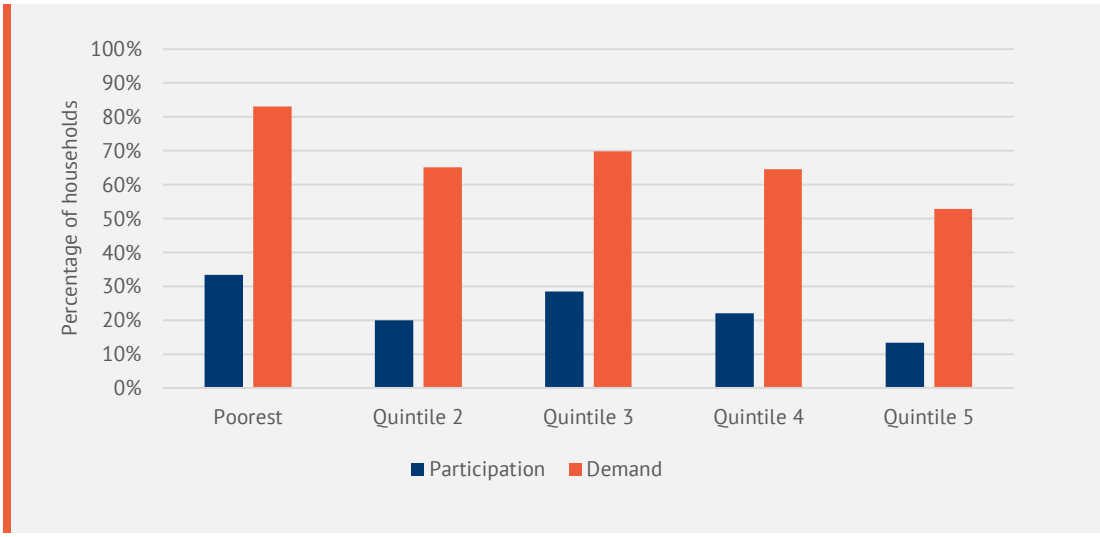
Country	Scheme	Coverage (as percentage of intended category)	Targeting Error	
			Exclusion errors with respect to intended recipients (percentage)	Exclusion of those in bottom 20% (percentage)
India	National Rural Employment Guarantee Act 2005	29	71	61

Source: own calculations using the IHDS 2012. Note: see Annex 2 for a detailed description of the methodology.

It may be that the exclusion of households from MGNREGA is not an error and that households simply chose not to access it. However, evidence from other research on MGNREGA shows that the quality of implementation varies significantly across India. For instance, Dutta et al (2014) have shown how the majority of people applying for work in Bihar State were unable to access the MGNREGA scheme (see Figure 21). Also, McCord (2005) has explained how, with self-targeted workfare schemes, often the poorest

households are unable to give up other income-generating activities due to the opportunity cost involved. Further, better-off households often send members who do not currently have employment while small households do not have labour to spare.[52]

Figure 21: Distribution across wealth quintiles of households accessing and applying for access to the MGNREGA scheme in Bihar State, India

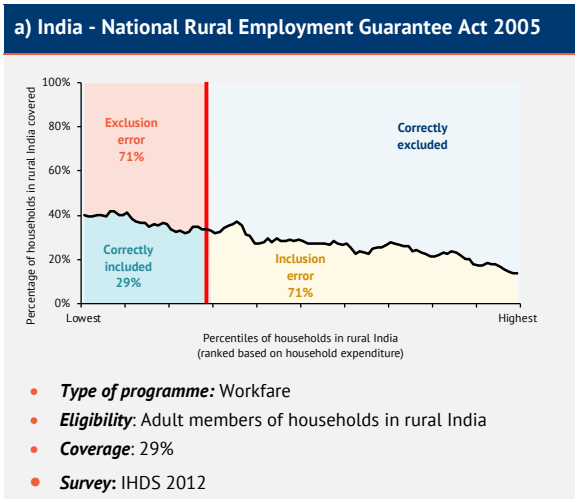


Source: Dutta et al (2014).

Therefore, the evidence indicates that, while self-targeting using low wage rates may appear to have a logic behind it as a means of encouraging only those living in extreme poverty to enter a workfare scheme, we did not find evidence of its effectiveness as a means of poverty targeting (although, admittedly, we had only one example in our research).

[52] Participation in workfare programmes has an opportunity cost since participants have usually given up another source of income, although it is likely to be lower than the payment offered by the workfare programme. For example, if a person earns US$1 per day on a workfare scheme, but could have earned US$0.75 from another activity, the effective transfer is only US$0.25.

Figure 22: Targeting effectiveness of a programme using self-targeting



Source: own calculations using the IHDS 2012. Note: see Annex 2 for a detailed description of the methodology.

5.2.5 Benefit testing

In theory, benefit testing should offer universal coverage through a combination of schemes (both tax-financed and funded from social insurance). However, the evidence from the two cases examined in the research – from Mexico and Vietnam – indicates that this is not necessarily the case. The results from both countries are set out in Table 7 and Figure 23.

Table 7: Summary of the results from programmes using benefit testing

Country	Scheme	Coverage (as percentage of intended category)	Targeting Error	
			Exclusion errors with respect to intended recipients (percentage)	Exclusion of those in bottom 20% (percentage)
Mexico	*Programa 65 y más*	60	40	29
Vietnam	Social Pension 80+ years	52	48	37

Source: own calculations using the national household surveys described in Table 1. Note: see Annex 2 for a detailed description of the methodology.

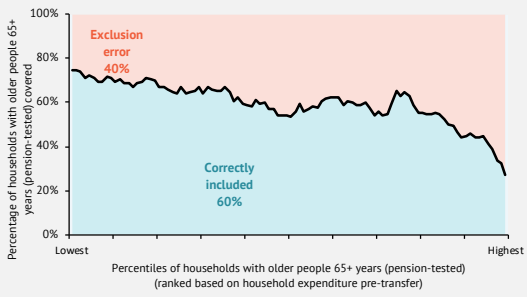
Mexico's *Programa 65 y Más* old age pension should be available to everyone aged 65 years and above not in receipt of another state pension above a specific value (i.e. social insurance and civil service pensions). Yet, only 60 per cent of the eligible population appear to access *Programa 65 y Más's* pension, meaning that 40 per cent are excluded. It is possible that the household survey does not incorporate accurate information on other

pensions which meant that we could not identify the eligible population. Alternatively, of course, our results may be correct and the recent decision by the Government of Mexico to turn the *Programa 65 y Más* scheme into a universal social pension may reflect that they recognise the errors with benefit testing. Their decision should reduce exclusion significantly.

Vietnam's experience with benefit testing appears similar to that of Mexico. Its social pension is offered to everyone aged 80 years and above who are not receiving the national social insurance pension. In reality, 48 per cent of those who are eligible for the social pension are not accessing it. Again, a move to universal social pension would most likely significantly improve the situation.

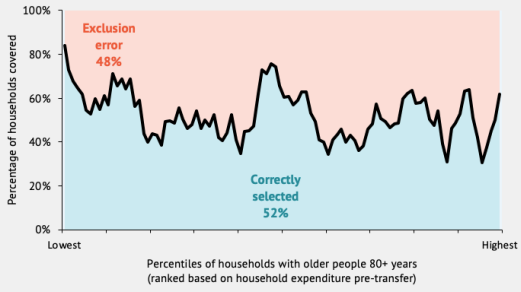
Figure 23: The targeting effectiveness of benefit-tested schemes

a) Mexico - Programa 65 y más



- ***Type of programme:*** Social pension
- ***Eligibility***: Adults aged 65 years and over not in receipt of another state pension
- ***Coverage***: 60%
- ***Survey***: ENIGH 2016

b) Vietnam - Social Pension 80 years and over



- ***Type of programme:*** Social pension
- ***Eligibility***: Adults aged 80 years and over not in receipt of another state pension
- ***Coverage***: 52%
- ***Survey***: VHLSS 2014

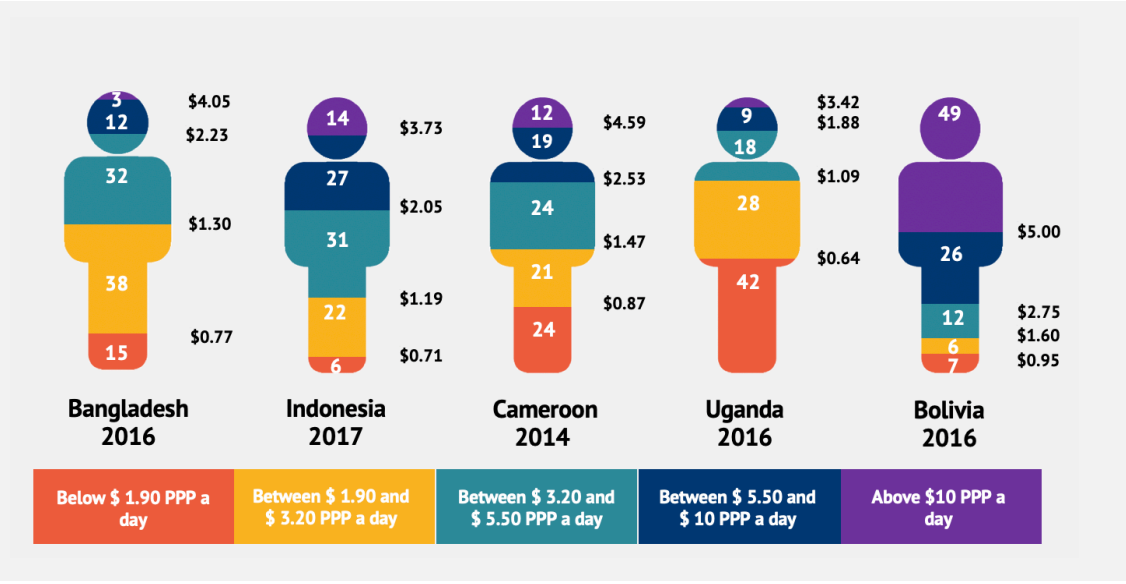
Source: own calculations using the national household surveys described in Table 1. Note: see Annex 2 for a detailed description of the methodology.

6 Poverty targeting in a world of constant change

There are many reasons for the limited effectiveness of poverty targeting and these are often particular to the specific scheme and local design of the mechanism. However, a key cause of ineffective targeting underpins all mechanisms everywhere: a fixed group known as 'the poor' is a fictional construct. This section explains why this is so.

While it is common to refer to 'the poor' and 'non-poor' when discussing targeting in social protection, as Figure 24 – which indicates the proportion of people living under different poverty lines – shows across five countries, most people in low- and middle-income countries are living in poverty, either under US$5.50 per day, measured in purchasing power parity (PPP) terms, or US$10 (PPP) per day.[53] By using purchasing power parity, it is possible to compare the standard of living with someone on the same income in the United States. In fact, as Figure 24 also shows, comparative real dollar values in low- and middle-income countries are much lower than the PPP values.

Figure 24: Proportion of people living under different poverty lines in five low- and middle-income countries, with figures in both nominal and purchasing power parity dollars



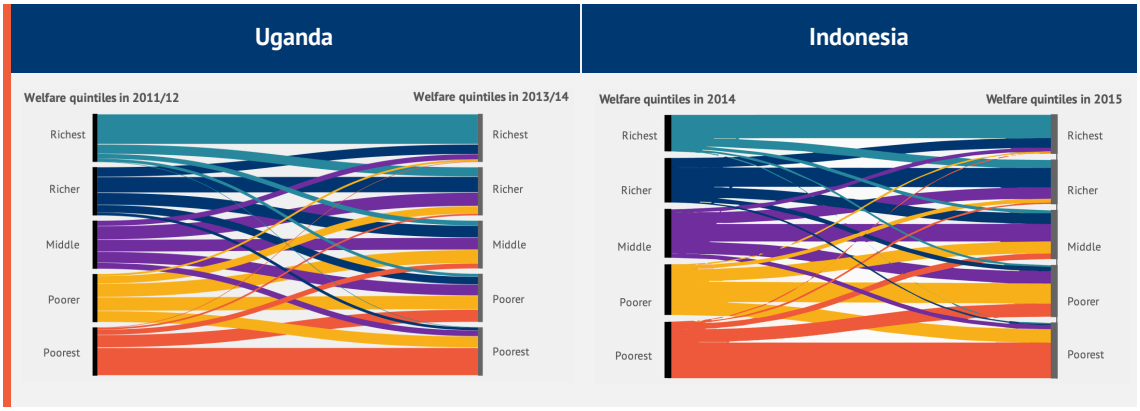
Source: own calculations using PovcalNet estimates for each country. Note: exchange rates are for the average of the year.

[53] These figures are meant to represent equivalent incomes in the United States of America (and, to provide clarity, the amount in actual dollars for each country are provided alongside each figure in the diagram).

In fact, Reddy and Lahoti (2015) point out that US$5.04 per day is the amount that the USA's Department for Agriculture determines is necessary for a person to enjoy a basic diet in the United States. Anyone with this level of income would not be able to purchase anything more. Indeed, they argue that US$5.00 (PPP) should, on this basis, be regarded as the international food poverty line. Further, Pritchett (2013) has proposed that the international poverty line should be set at US$10 (PPP) per day, given that someone living on this amount would still be regarded as living in extreme poverty in the USA. Therefore, it would be reasonable to argue that few people in low- and middle-income countries have escaped poverty, and most would benefit from social protection.

Furthermore, while the term 'the poor' suggests a fixed group of people, in reality individual and household incomes (and consumption) are highly dynamic. Figure 25 indicates changes in the ranking of households in Indonesia and Uganda over a period of one year in the former and two years in the latter. The diagrams show – on the left-hand side of each figure – where households were ranked across consumption quintiles, from poorest to richest, in the initial year and the quintile in which they were found one or two years later. It shows a significant volatility in consumption with a high proportion of households moving between consumption quintiles over a very short period of time, including to and from the poorest quintile. For example, in Uganda, only 46 per cent of households that were in the poorest quintile in 2013 had been in the poorest quintile in 2011; and, in Indonesia, the figure among households with children was 48 per cent between 2014 and 2015. In both countries, there are examples of households in the highest quintile falling into the lowest quintile over the two periods.

Figure 25: Movement of households across consumption quintiles over one year in Indonesia and two years in Uganda

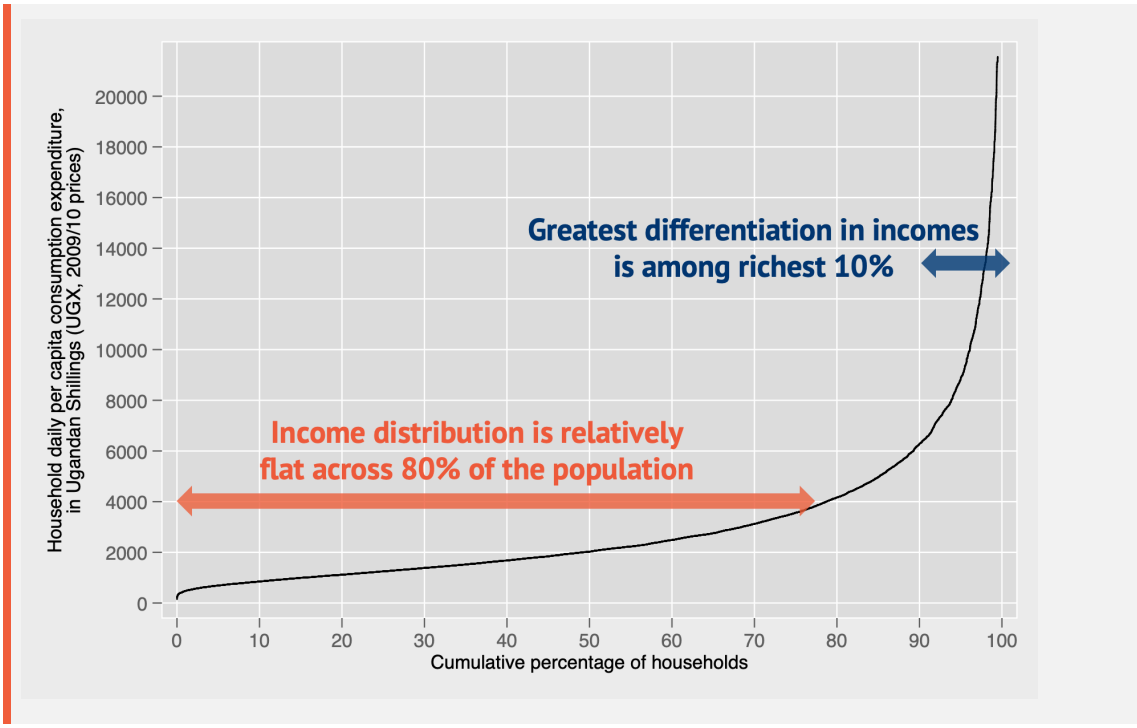


Source: Analysis undertaken by Development Pathways of panel datasets in each country, in Kidd and Gelders (2016) and Gelders and Abu-el-Haj (2017). Note: analysis of Indonesia includes households with children.

In fact, it is noticeable that, in both countries, across the 2nd, 3rd and 4th quintiles, there is very significant movement. This is because, in most countries, there is little difference in

the relative consumption (or income) of households below the wealthiest 10 per cent of the population. Similar to the situation described above in South Africa – and common to most countries – Figure 26 shows how, across the majority of households in Uganda, the distribution of incomes is relatively flat: only among the wealthiest 10 per cent are there greater differentiations in income. So, a small shift in income or consumption could easily change the ranking of a household: for example, a 20 per cent reduction in per capita income in a household ranked at the 50th percentile could move it down to the 38th percentile. And, as explained above, given the prevalence of households experiencing shocks – even small ones – these changes happen frequently.

Figure 26: Wealth distribution of households in Uganda



Source: own calculations using the Uganda National Household Survey, 2016-17.

Therefore, the generalised poverty in low- and middle-income countries, combined with volatile incomes, means that static groups known as 'the poor' and 'non-poor' do not exist. A fictional construct is not a sound basis for the development of social policy nor, in particular, for decisions to use poverty targeting in social protection.[54] Indeed, the dynamic nature of individual and household incomes makes it very difficult to undertake poverty targeting accurately and is a key factor explaining the errors found in the research.

[54] See Knox-Vydmanov (2014) for a further discussion.

7 Conclusion

As argued at the beginning of this paper, it is important that debates on targeting are informed by evidence. And, the evidence from this research clearly shows that universal and affluence-tested schemes are much more effective than poverty-targeted programmes in reaching both their intended recipients and those living in poverty. This should be an unsurprising finding. However, the scale of the errors with poverty targeted schemes is, perhaps, more unexpected. There is no evidence at all that poverty targeting in low- and middle-income countries can be undertaken with any degree of accuracy. Indeed, if a poverty-targeted scheme were to have an exclusion error of 50 per cent, that should be regarded as an exceptionally good performance.

Our analysis also calls into question the use of 'benefit incidence' as a reliable measure of targeting effectiveness. Indeed, its continuing use should be regarded as a deliberate means of hiding the inaccuracies of poverty targeting. For example, the World Bank (2017b) has claimed that 70 per cent of Indonesia's PKH recipients were in the poorest 40 per cent of the population, which sounds like a relatively good performance. In fact, our research demonstrated a similar result, with 70.2 per cent of recipients found in the poorest 40 per cent of the target population. However, the programme has an exclusion error of 82 per cent. Similarly, the World Bank (2017a) claimed that about 75 per cent of the recipients of the Benazir Income Support Programme (BISP) belonged to the bottom 40 per cent of population which, again, to the untrained eye appears a good result. In fact, the IMF (2017) stated that 'Overall, BISP is perceived to be targeted relatively fairly and protect the poorest households.' This positive impression, however, contrasts with the exclusion error of 73 per cent found in our research.

The results from the research are further proof of the old adage that programmes for the poor are poor-quality programmes. And, the targeting mechanisms used in many low- and middle-income countries are particularly problematic. It is difficult to imagine that mechanisms such as proxy means testing or community-based targeting would ever be allowed in Europe and, indeed, as Section 5.2.2 indicated, the use of algorithms alone to select people for schemes has recently been banned in the European Union. Nonetheless, the same European countries are happy to promote these poor-quality and ineffective methods across Africa, Asia and Latin America.

The belief among some advocates of poverty targeting that technology will bring about improvements is also not borne out by the evidence: even in relatively advanced Latin America contexts with 'cutting-edge' Social Registries, the errors are high. Any significant improvements are unlikely to happen.

7 Conclusion

If governments and international agencies are really committed to 'leaving no-one behind' and ensuring that the right to social security is fully realised, the evidence from our research demonstrates that it will be necessary to support universal social protection programmes. Of course, universal programmes will require a higher level of investment than those using poverty targeting but the simple truth is that quality costs.[55] Indeed, the only strong rationale for poverty targeting is to reduce costs. Yet, this argument is only valid within a world view favouring low public spending and low taxes, where the aim is to benefit the wealthy – thorugh low taxes – rather than those living in poverty.[56] Outside this world view, many would argue that higher levels of investment in social security – as long as schemes are well-designed – is a good thing. Higher investment can maximise impacts and help generate greater economic growth.[57] It is no coincidence that high-income countries – with historically successful economies – invest an average of 12 per cent of GDP in social security.

Another argument put forward by advocates of poverty targeting is that, when budgets are limited, poverty targeting will ensure that those living in poverty will receive higher transfer values. Yet, there is also limited evidence to support this claim. In reality, because inclusive – in particular universal – schemes are popular with the majority of citizens, governments, in a democratic context, are more likely to invest in them than in poverty-targeted programmes. As a result, they will also allocate higher transfer values. Therefore, families living in poverty are likely to benefit more from universal schemes than targeted programmes as a result of both higher transfer values and a much greater likelihood of inclusion.[58]

If policy makers want effective social protection, they have to be willing to invest in inclusive, lifecycle social protection systems. These are systems that address the risks, challenges and contingencies that all of us face across the lifecycle, offering schemes such as universal child benefits, disability benefits and old age pensions. Poor relief schemes – such as targeted and conditional cash transfers and workfare programmes – are an outdated and ineffective model to use as the basis of social security systems. Poverty targeting may still have its place among small, residual programmes but its failure as the basis of an effective national social security system has been laid bare by this research. It is time to change.

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[55] See Kidd (2017b) for a further explanation of how more effective social protection requires higher levels of investment.
[56] See Kidd (2018b) and (2018c) for further explanation.
[57] See Kidd and Tran (2017).
[58] For further information on the political economy of targeting, see World Bank (1990), Sen (1995), Moene and Wallerstein (2001), Pritchett (2005) and Kidd (2015b).

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Annex 1 Summary of programmes and targeting errors

Country	Scheme	Intended category and recipients	Coverage (as percentage of intended category)	Survey Dataset	Programme Type	Targeting Error	
						Exclusion errors with respect to intended recipients (percentage)	Exclusion of those in bottom 20% (percentage)
Albania	*Ndihme Ekonomike*	Families living in poverty	8.3	LSMS 2012	Poor relief	72	80
Armenia	Family Benefits	Families with children living in poverty	19	HILCS 2015	Poor relief	49	50
Bangladesh	Old Age Pension	Women aged 62 years and above and men aged 65 years and above, living in poverty	18	HIES 2016	Old Age Pension	59	62
Bolivia	*Renta Dignidad*	Adults aged 60 years and over	92.3	EH 2015	Old Age Pension	8	8
Bolivia	*Bono Juancito Pinto*	Children attending public primary schools for formal education, youth alternative and/or special education	92	EH 2015	School stipend	8	6
Brazil	*Bolsa Família*	Families living in poverty	13.7	PNAD 2017	Poor relief CCT	44	51
Colombia	*Familias en Acción*	Households with children living in poverty	23.5	ECV 2017	Poor relief CCT	60	60

Annex 1 Summary of programmes and targeting errors

Colombia	*Programa Colombia Mayor*	Women aged 54 years and over and men aged 59 years and over, living in poverty	19	ECV 2017	Old Age Pension	61	61
Ecuador	*Bono de Desarrollo Humano*	Households living in poverty with children aged 16 years and under	18.3	ENCV 2014	Poor relief CCT	48	50
Ecuador	Social Pension	Adults aged 65 years and over living in poverty	45.9	ENCV 2014	Old Age Pension	30	19
Ethiopia	Productive Safety Net Programme	Chronically food insecure families in rural Ethiopia	12.2	ESS 2015	Poor relief and workfare	81	83
Ethiopia	Productive Safety Net Programme (direct support)	Chronically food insecure households in rural Ethiopia that are labour constrained	7.7	ESS 2015	Poor relief	80	86
Ethiopia	Productive Safety Net Programme (public works)	Chronically food insecure households with labour capacity in rural Ethiopia	9.1	ESS 2015	Workfare	87	88
Georgia	Old Age Pension	Women aged 60 years and over and men aged 65 years and over	98.5	WMS 2015	Old Age Pension	1	0
Georgia	Targeted Social Assistance	Families living in poverty	14.9	WMS 2015	Poor relief	53	58
Ghana	Livelihood Empowerment Against Poverty	Households living in poverty	0.9	GLSS7 2017	Poor relief	95	97
Guatemala	*Mi Bono Seguro*	Families living in poverty with children aged 15 years and under	6.8	ENCOVI 2014	Poor relief CCT	96	95
India	Indira Gandhi National Old Age Pension Scheme	Adults aged 60 years and above, living in poverty	21.1	IHDS 2012	Old Age Pension	68	68

Annex 1 Summary of programmes and targeting errors

India	National Rural Employment Guarantee Act 2005	Adult members of households in rural India	28.6	IHDS 2012	Workfare	71	62
India	Below Poverty Line	Households living in poverty	36.3	IHDS 2012	Registry	54	51
Indonesia	Program *Keluarga Harapan*	Households with children or pregnant or lactating women living in poverty	7	SUSENAS 2017	Poor relief CCT	82	85
Indonesia	*Kartu Perlindungan Sosial*	Households living in poverty	14.5	SUSENAS 2017	Registry	71	73
Indonesia	*Pintar*	Children aged between 6 and 17 years living in poverty and attending school	17.6	SUSENAS 2017	School stipend	56	66
Kenya	Hunger Safety Net Programme	Households in Northern Kenya living in poverty	19.8	KIHBS 2015	Poor relief	70	69
Mexico	*Prospera*	Households living in poverty	17.8	ENIGH 2016	Poor relief CCT	54	56
Mexico	*Programa 65 y más*	Adults aged 65 years and over not in receipt of another state pension	59.6	ENIGH 2016	Old Age Pension	40	29
Mongolia	Child Money Programme	Children	98.4	HSES 2016	Child benefit	2	1
Pakistan	Benazir Income Support Programme	Families living in poverty	8.2	HIES 2015	Poor relief	73	79
Peru	*Juntos*	Households with children aged 19 years and under and/or pregnant and breastfeeding women living in poverty	16	ENAHO 2017	Poor relief CCT	46	50
Philippines	*Pantawid Pamilyang Pilipino* Program	Households with children aged 18 years and under and/or pregnant women living in poverty	23.4	APIS 2014	Poor relief CCT	48	46

Annex 1 Summary of programmes and targeting errors

Rwanda	*Vision 2020 Umurenge Programme*	Households living in poverty	3.1	EICV 2014	Poor relief and workfare	95	96
Rwanda	Vision 2020 Umurenge Programme (public works)	Households living in poverty with labour capacity	1.6	EICV 2014	Workfare	97	98
Rwanda	*Vision 2020 Umurenge Programme* (direct support)	Households living in poverty that are labour constrained	10	EICV 2014	Poor relief	90	89
Rwanda	*Ubudeh*e (groups 1 and 2)	Households living in poverty	30.1	EICV 2014	Registry	53	49
South Africa	Child Support Grant	Children in low income families	71	GHS 2017	Child benefit	13	0
South Africa	Old Age Grant	Adults aged 60 years and over with low incomes and/or assets valued below a specified threshold	84	GHS 2017	Old Age Pension	8	0
Sri Lanka	*Samurdhi*	Households living in poverty	19	HIES 2016	Poor relief	58	59
Sri Lanka	Senior Citizens' Allowance	Households with adults aged 70 years and above, living in poverty	23	HIES 2016	Old Age Pension	58	57
Uruguay	*Asignaciones Familiares*	Families with children aged 17 years and under and/or people with disabilities living in poverty	44.9	ECH 2016	Poor relief CCT	29	17
Uzbekistan	Family and Childcare Allowances	Households with children aged between 0 and 14 years living in poverty	14.5	L2CU 2018	Poor relief	71	69
Uzbekistan	Childcare Allowance	Households with children aged between 0 and 1 year living in poverty	23.4	L2CU 2018	Poor relief	57	59

Uzbekistan	Family Allowance	Households with children aged between 2 and 14 years living in poverty	7.6	L2CU 2018	Poor relief	83	84
Uzbekistan	Low-Income Allowance	Households living in poverty	0.9	L2CU 2018	Poor relief	93	98
Vietnam	Social Pension 80+ years	Adults aged 80 years and over not in receipt of another state pension	52.4	VHLSS 2016	Old Age Pension	48	38
Vietnam	Poor List	Households living in poverty	10.6	VHLSS 2014	Registry	49	63

Annex 2 Detailed description of the data analysis methodology

This study aimed to estimate the targeting effectiveness of tax-financed social protection programmes and registries. This was carried out by undertaking an analysis of national household surveys that included questions on social protection programme participation and measures of well-being such as income and consumption expenditure levels. Overall, we investigated 27 national household surveys and 46 schemes and registries across 27 developing countries in Latin America, Africa and Asia. However, we had to exclude 4 of these schemes for different reasons. The schemes excluded were: the *Asignación Universal por Hijo* in Argentina because it was not possible to identify the children who were eligible – children living in households where working-age adults were in the informal sector; the *Benefício de Prestação Continuada* in Brazil because, similarly, we could not identify the older people and people with disabilities who were eligible (the absence of data on disability); the Cash Transfer for Orphans and Vulnerable Children and Older Persons Cash Transfer in Kenya because there were not sufficient recipient households identified; and, the Social Cash Transfer in Malawi because, again, the number of recipient households was too small. We also looked at 3 combinations of schemes, they were: Ethiopia's combined direct support and workfare schemes within PSNP; Rwanda's combined direct support and workfare schemes within VUP; and, Uzbekistan's Family and Childcare Allowances.

Two measures of targeting effectiveness were used in this study. The first measure estimates for a particular scheme the proportion of households including intended recipients not covered by the programme. We define intended recipient households as those that would have been reached if the programme had been perfectly targeted. For example, if a poverty-targeted programme reaches 5 per cent of households in the programme's intended category, then we consider the intended recipient households to be the poorest 5 per cent in the intended category. In schemes that use universal selection, this definition is slightly altered. Instead, we consider all households in the intended category to be intended recipients.

Following Ravallion et al's (2018) annotation, this first measure of targeting effectiveness of scheme s in year t can be formally represented as,

$$TE_{st}^{1} = \frac{\sum_{i}^{N_{st}} w_{ist} 1_{\{D_{st}=0 \mid y_{ist}<z_{st}\}}}{\sum_{i}^{N_{st}} w_{ist} 1_{\{y_{ist}<z_{st}\}}},$$

where w_{ist} denotes the sample weight of household i in the intended category of scheme s in year t; households are indexed from 1 to N_{st}, and N_{st} is the total sample size of all

households in the intended category, such that $\sum_{i}^{N_{st}} w_{ist} = 1$; D_{st} is a Boolean variable with 1 representing programme participation at the household level and 0 otherwise; y_{ist} is a household i's level of welfare as measured by income or consumption expenditure; finally, z_{st} is the corresponding level of welfare when the inverse empirical cumulative distribution function of y_{st}, $F^{-1}(p)$, is measured against the scheme's coverage of the intended category, p. The measure of targeting effectiveness ranges from 0 to 1 with $TE_{st}^{1} = 0$ meaning that the programme reached all of its intended recipients. Conversely, $TE_{st}^{1} = 1$ would mean that the programme does not reach any of its intended recipients.

The second measure used in this study looks at the targeting effectiveness of programmes in reaching the poorest 20 per cent of their intended category, in other words the proportion of the poorest 20 per cent of households with a member of the intended category who were excluded from the scheme. Formally, the metric is computed in a similar way to TE_{st}^{1}, but z_{st}, is fixed to the corresponding level of welfare when p is equal to 0.2 in the inverse empirical cumulative distribution function of y_{st}, $F^{-1}(p)$. This second measure also ranges from 0 to 1 with $TE_{st}^{2} = 0$ meaning that the programme reached all of those in the in the poorest 20 per cent of the intended category. And, conversely, $TE_{st}^{2} = 1$ would mean that the programme does not reach any of the poorest in the intended category.

In order to estimate targeting effectiveness using household surveys it was, therefore, important to understand clearly how each programme works as well as the intended category for each programme. This review was undertaken by going through official programme documentation and existing databases for Latin America, Africa, Asia, social pensions and other relevant literature. The databases used were ECLAC's database of tax-financed social protection programmes in Latin America, Cirillo and Tebaldi's (2016) database for programmes in Africa and HelpAge International's Social Pensions Database (Pension Watch).

In the data analysis, we used the household as our unit of the analysis such that, if a programme is intended for individual recipients, we identify their households as participating in the programme. Therefore, if there were two members in a household receiving a benefit from the same scheme, we count only one household as receiving the benefit. This was done for two reasons. First, it creates consistency when evaluating programmes across the different intended categories: some programmes were intended for individuals – such as older people – while others are intended for families or households. The second reason has to do with the selected measure of well-being. Across the datasets we used household aggregate measures of well-being and, in most cases, it was not possible to account for the intra-household distribution of welfare in the data. All

results were weighted with household sample weights to account for the complexity of each of the household surveys.

Two measures of monthly household welfare were used in this analysis: household per capita consumption expenditure and household per capita income. When both measures were available, we opted for the former. Where possible we applied the same aggregate measures used by the national statistic offices of each country.[59] There were some exceptions where the aggregate welfare measure variables were not available in the dataset. In such instances we constructed the aforementioned variables following closely the methodology described in the survey documentation. As is customary with these exercises, the exact reported figures were not always replicated, but we are confident that we were able to construct a valid ranking measure of welfare.

In order to account for differences in household rankings pre- and post-programme participation, we deducted from our measure of welfare the monthly per capita transfer value received by the household. Although this is straightforward when using income as the measure of welfare, it is not so when it comes to expenditure given that households may have a non-zero marginal propensity to save. In this exercise, we assumed that all transfer values are consumed and that no savings are made. Although this is a strong assumption and unlikely to happen across all households in the wealth spectrum, it is more likely to occur among households in the lower end of the wealth spectrum, which are the households that poverty-targeted programmes aim to reach.

Not all datasets provide estimates of transfer values received. For datasets that do not include programme transfer values we imposed the transfer values set in the year of the survey. Table 8 provides an overview of the welfare measured used, the survey-specific assumptions used to construct an ex-ante ranking measure of welfare, and how the intended category was identified in the dataset.

In addition to estimating the targeting effectiveness of each scheme, this study provided estimates of programme coverage by welfare percentiles. These were shown as scheme-specific graphs across Sections 5. However, coverage estimates in the graphs were smoothed out to remove sharp fluctuations in neighbouring estimates. The black lines in the graphs are rolling average curves of programme coverage for each percentile, where each point in the curve is a simple average of the coverage estimate in that percentile in addition to the coverage estimates of the adjacent four percentiles (two to each side).

[59] If country specific adult equivalent scales are used, we rescale the welfare variable to be measure household per capita estimates.

Table 8: Data and scheme-specific assumptions on welfare variable and intended categories

Country	Programme	Survey	Welfare variable	Pre-transfer (Yes/No)	Note on transfer values	Scheme's intended category and recipients	Intended category in dataset
Albania	*Ndihme Ekonomike*	LSMS 2012	Household expenditure	Yes	Imputed transfer values. Used the midpoint of the reference range in the social protection national strategy 2015-2020	Families living in poverty	All households
Armenia	Family Benefits	HILCS 2015	Household expenditure	Yes	Used values from survey	Families with children living in poverty	Households with children aged 17 years and under
Bangladesh	Old Age Pension	HIES 2016	Household expenditure	Yes	Used values from survey	Women aged 62 years and above and men aged 65 years and above, living in poverty	Households with female members aged 62 years and above, and male members aged 65 years and above
Bolivia	*Renta Dignidad*	EH 2015	Household income	Yes	Used values from survey	Adults aged 60 years and over	Households with members aged 60 years and over
Bolivia	*Bono Juancito Pinto*	EH 2015	Household income	Yes	Imputed transfer values. Used values from ECLAC's social protection database for the year of the survey	Children attending public primary schools for formal education, youth alternative and/or special education	Households with children aged between 6 and 10 years of age and in the first 5 years of public school education
Brazil	*Bolsa Família*	PNAD 2017	Household income	Yes	Used values from survey	Families living in poverty	All households
Colombia	*Familias en Acción*	ECV 2017	Household income	Yes	Used values from survey	Households with children living in poverty	Households with children aged 17 years and under
Colombia	*Programa Colombia Mayor*	ECV 2017	Household income	Yes	Used values from survey	Women aged 54 years and over and men aged 59 years and over, living in poverty	Households with female members aged 54 years and above and male members aged 59 years and above
Ecuador	*Bono de Desarrollo Humano*	ENCV 2014	Household expenditure	Yes	Used values from survey	Households that are living in poverty with children aged 16 years and under	Households with children aged 16 years and under or with members aged 65 years and over
Ecuador	Social Pension	ENCV 2014	Household expenditure	Yes	Used values from survey	Adults aged 65 years and over living in poverty	Households with member(s) aged 65 years and over
Ethiopia	Productive Safety Net Programme	ESS 2015	Household expenditure	Yes	Used values from survey	Chronically food insecure families in rural Ethiopia	All households in rural areas

Ethiopia	Productive Safety Net Programme (direct support)	ESS 2015	Household expenditure	Yes	Used values from survey	Chronically food insecure households in rural Ethiopia that are labour constrained	Households in rural areas that are labour constrained (where the head and spouse is older than 60 years or with some form of functional limitation as outlined by the Washington Group short set disability questions)
Ethiopia	Productive Safety Net Programme (public works)	ESS 2015	Household expenditure	Yes	Used values from survey	Chronically food insecure households with labour capacity in rural Ethiopia	Households in rural areas with labour capacity (where the head and spouse are of working age 18 to 59 years with no functional limitations as identified by the Washington Group short set of questions)
Georgia	Old Age Pension	WMS 2015	Household expenditure	Yes	Used values from survey	Women aged 60 years and over and men aged 65 years and over	Households with female member(s) aged 60 years and over or male member(s) aged 65 years and over
Georgia	Targeted Social Assistance	WMS 2015	Household expenditure	Yes	Used values from survey	Families living in poverty	All households
Ghana	Livelihood Empowerment Against Poverty	GLSS7 2017	Household expenditure	Yes	Used values from survey	Households that living in poverty	All households
Guatemala	*Mi Bono Seguro*	ENCOVI 2014	Household expenditure	Yes	Used values from survey	Families living in poverty with children aged 15 years and under	Households with children aged 15 years and under
India	*Indira Gandhi* National Old Age Pension Scheme	IHDS 2012	Household expenditure	Yes	Imputed transfer values. Used benefit values set in NSAP's website	Adults aged 60 years and above, living in poverty	Households with member(s) aged 60 years and over
India	National Rural Employment Guarantee Act 2005	IHDS 2012	Household expenditure	No	Given the complexity of scheme's payment rollout, it was not feasible to imput a transfer value or accurately infer from the dataset	Adult members of households in rural India	All households in rural areas
India	Below Poverty Line	IHDS 2012	Household expenditure	No	No value as it is a card signifying eligibility (registry)	Households living in poverty	All households
Indonesia	*Program Keluarga Harapan*	SUSENAS 2017	Household expenditure	Yes	Imputed transfer values. Used the minimum transfer values	Households with children or pregnant or lactating women living in poverty	Households with children aged 17 years and under
Indonesia	*Kartu Perlindungan Sosial*	SUSENAS 2017	Household expenditure	No	No value as it is a card signifying eligibility (registry)	Households living in poverty	All households

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Indonesia	*Pintar*	SUSENAS 2017	Household expenditure	Yes	Used values from survey	Children aged between 6 and 17 years living in poverty and attending school	Households with children of school age (aged between 6 and 17 years)[60]
Kenya	Hunger Safety Net Programme	KIHBS 2015	Household expenditure	Yes	Imputed transfer values. Used Ksh 2,700 as the benefit value	Households in Northern Kenya that are living in poverty	Households located in Marsabit, Mandera, Turkana, and Wajir
Mexico	*Prospera*	ENIGH 2016	Household income	Yes	Used values from survey	Households living in poverty	All households
Mexico	*Programa 65 y más*	ENIGH 2016	Household expenditure	Yes	Used values from survey	Adults aged 65 years and over not in receipt of another state pension	Households with member(s) aged 65 years and over, and are not receiving any other form of state old age pension
Mongolia	Child Money Programme	HSES 2016	Household expenditure	Yes	Used values from survey	Children	Households with children aged 17 years and under
Pakistan	Benazir Income Support Programme	HIES 2015	Household expenditure	Yes	Used values from survey	Families living in poverty	Households with children aged 17 years and under
Peru	*Juntos*	ENAHO 2017	Household expenditure	Yes	Used values from survey	Households with children aged 19 years and under and/or pregnant and breastfeeding women living in poverty	Households with children aged 19 years and under
Philippines	*Pantawid Pamilyang Pilipino* Program	APIS 2014	Household expenditure	Yes	Used values from survey	Households with children aged 18 years and under and/or pregnant women living in poverty	Household with children aged 17 years and under
Rwanda	*Vision 2020 Umurenge Programme*	EICV 2014	Household expenditure	Yes	Used values from survey	Households living in poverty	All households
Rwanda	*Vision 2020 Umurenge Programme* (public works)	EICV 2014	Household expenditure	Yes	Used values from survey	Households living in poverty with labour capacity	All households with labour capacity
Rwanda	*Vision 2020 Umurenge Programme* (direct support)	EICV 2014	Household expenditure	Yes	Used values from survey	Households living in poverty that are labour constrained	Households that are labour constrained (using variable in dataset refering to the number of members in the household that are able to work)
Rwanda	*Ubudehe* (groups 1 and 2)	EICV 2014	Household expenditure	No	No value imputed as it is a registry	Households living in poverty	All households

[60] Since 90 per cent of children were attending school in Indonesia, the analysis examined all children of the appropriate age.

South Africa	Child Support Grant	GHS 2017	Household income	Yes	Imputed transfer values. Used values released by SASSA for survey year	Children in low income families	Households with children aged 17 years and under
South Africa	Old Age Grant	GHS 2017	Household income	Yes	Imputed transfer values. Used values released by SASSA for survey year	Adults aged 60 years and over with low incomes and/or assets valued below a specified threshold	Households with members aged 60 years and over
Sri Lanka	*Samurdhi*	HIES 2016	Household expenditure	Yes	Used values from survey	Households living in poverty	All households
Sri Lanka	Senior Citizens' Allowance	HIES 2016	Household expenditure	Yes	Used values from survey	Households with adults aged 70 years and above, living in poverty	Households with members aged 70 years and above
Uruguay	*Asignaciones Familiares*	ECH 2016	Household income	Yes	Used values from survey	Families with children aged 17 years and under and/or people with disabilities living in poverty	Households with children aged 17 years and under
Uzbekistan	Family and Childcare Allowances	L2CU 2018	Household income	Yes	Used values from survey	Households with children aged between 0 and 14 years living in poverty	Households with children aged 14 years and under
Uzbekistan	Childcare Allowance	L2CU 2018	Household income	Yes	Used values from survey	Households with children aged between 0 and 1 year living in poverty	Households with children aged between 0 and 1 year
Uzbekistan	Family Allowance	L2CU 2018	Household income	Yes	Used values from survey	Households with children aged between 2 and 14 years living in poverty	Households with children aged between 2 and 14 years
Uzbekistan	Low-Income Allowance	L2CU 2018	Household income	Yes	Used values from survey	Households living in poverty	All households
Vietnam	Social Pension 80+ years	VHLSS 2016	Household expenditure	Yes	Used values from survey	Adults aged 80 years and over not in receipt of another state pension	Households with member(s) aged 80 years and over not receiving another state old age pension
Vietnam	Poor List	VHLSS 2014	Household expenditure	No	No value imputed as it is a registry	Households living in poverty	All households

Development Pathways is committed to bold and innovative thinking on social policy. Our aim is to provide creative, evidence-based and context-specific solutions to the social and economic challenges facing low- and middle-income countries.

Act Church of Sweden defends people's dignity and rights – through humanitarian and long-term development work, church collaboration, and advocacy. We work together with churches and actors from the civil society and belong to the ACT Alliance – Action by Churches Together.

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