Why social benefits fail to target poverty. Empirical evidence on target efficiency of the Italian minimum income scheme

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Abstract

Poverty is associated with severe consequences in terms of individual and social well-being and should be a primary concern for policymakers: while many public policies indirectly affect poverty outcomes, it is widely agreed that minimum income schemes (MISs) are one of the most important tools for poverty alleviation. Targeting the poor, however, is a very difficult task, further complicated by the fact that no unambiguous definition of poverty exists. This paper thus contributes to the literature in two ways: i) it proposes a novel theoretical framework to evaluate the target efficiency of MISs; ii) it exploits a unique dataset for Italy in 2019 to provide an empirical assessment of the target efficiency of the recently introduced Italian minimum income scheme – Reddito di Cittadinanza (RdC). A key assumption is that the target of the RdC is the poor population according to the official consumption-based absolute poverty indicator. The results are quite shocking: only 25% of poor households received RdC in 2019, while, from a different perspective, just over 40% of recipient households were also poor. Since, in line with the proposed theoretical framework, such misalignment may depend on both the inadequacy of the RdC eligibility requirements and the imperfections of the absolute poverty indicator, the empirical analyses shed some light on both of these issues. A few results are worth mentioning: first, almost one-quarter of poor households not receiving the RdC declare to have an adequate level of well-being and do not apply to any welfare transfer or facilitation, denoting some flaw in the poverty indicator (expenditure underestimation); second, and conversely, overall expenditure is likely to be overestimated for one-fifth of non-poor households receiving the RdC; finally, almost 90% of poor households with a low level of self-perceived well-being are excluded by design, highlighting excessive strictness of eligibility requirements.

Keywords: Absolute Poverty, Minimum income schemes, Target efficiency

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1 Introduction

Poverty is a social outcome with intolerable consequences and should be firmly contrasted by welfare states. To this aim, as full employment abandoned the policy agenda after the neoliberal turn of the 1980s and wage flexibility became the main mechanism to absorb macroeconomic imbalances in many advanced (and especially European) economies, minimum income schemes (MISs) have come to the fore in recent years (Figari et al. 2013, Marx et al. 2016, European Parliament 2017, Raitano et al. 2021). Since MIS are typically residual policies with limited budgetary resources, evaluating their ability to correctly identify and reach the poor – i.e., their target efficiency – has become increasingly important. The task, however, is very complicated for several reasons. One specific issue often neglected by the literature is that no unique poverty definition exists: different indicators often disagree on poverty identification and confound evaluations of the targeting performance of MISs (Notten 2016).

This paper takes stock of these complexities and innovates the literature in two ways. First, it proposes to frame the evaluation of the target (in)efficiency of MISs within a novel conceptual scheme. Second, it exploits a unique dataset for Italy in 2019 to evaluate the target efficiency of the recently introduced Italian minimum income scheme – Reddito di Cittadinanza (RdC). The Italian case is indeed extremely interesting for two main reasons: besides being ad advanced economy with a relatively high poverty rate (AROP above 20% in 2019), Italy is also the only European country estimating an official consumption-based absolute poverty indicator. This seems particularly relevant since these types of poverty indicators have been elsewhere found to be closely correlated to economic disadvantage (Meyer and Sullivan 2009, Meyer and Sullivan 2011, Meyer and Sullivan 2012 for the US, Brewer et al. 2017 for the UK). In the empirical assessment of the target efficiency of the RdC we thus use the official consumption-based absolute poverty indicator as a benchmark. In other words, we explore to what extent the RdC is able to effectively target households in absolute poverty. While fighting absolute poverty is surely not the only policy goal of the RdC, this choice is nonetheless justified on both economic and institutional grounds (for instance, the National Social Security Institute declared in a parliamentary hearing held in March 2019 that, among other things, the RdC should be evaluated according to its ability to reduce absolute poverty, see Section 2).

Besides providing general evidence on the overlap between absolute poverty and RdC receipt, we also explore in detail the household characteristics associated with the areas where the two concepts disagree – i.e., the sets of poor but not receiving households (I-type errors) and non-poor but receiving households (II-type errors). We argue this is an important first step in distinguishing the flaws of the benchmark poverty indicator used from the design and administrative failures of the MIS. What remains of this paper is thus structured as follows: the general conceptual framework that guides the analysis is presented in Section 2, together with some discussion of what may be expected on the overlap between the population in absolute poverty and RdC recipients. Section 3 presents the dataset that made all the empirical analyses possible and section 4 presents the main results and discusses the possible determinants of I- and II-type errors. Section 5 concludes.

2 Minimum income schemes and shared poverty measures: conceptual framework

The targeting performance of means-tested public programmes has been at the heart of a large body of literature. For instance, Figari et al. (2013) use microsimulation techniques to evaluate coverage[1] and adequacy of MISs in 14 European countries, Nelson and Nieuwenhuis (2021) propose a comprehensive sequential framework to analyse benefit coverage based on the distinction between actual and potential recipients, Gorjón and Villar (2019) provide an extensive evaluation of the Renta de Garantía de Ingresos (RGI) – the MIS of the Basque region in Spain - in 2016, Bárcena-Martín et al. (2018) explore whether targeting low incomes or children is more effective in reducing child poverty finding evidence for the second case, Notten and Gassmann (2008) assess the target efficiency and the poverty reduction effects of means-tested versus universal child allowances in Russia using the policy shift in 2000 as a case study. All these contributions are extremely valuable. However, assessing the target efficiency of MIS – i.e., means-tested monetary transfers targeted to the poor – requires taking into consideration an additional very specific issue, namely that no unique poverty definition exists. Different assumptions on what constitutes an acceptable minimum living standard and how best to measure it lead to different poverty indicators, which, in turn, define (sometimes very) different sets of poor individuals. As a consequence, the targeting performance of a given MIS may heavily depend on the chosen benchmark poverty indicator (target group) with potentially confusing policy implications. The contribution by Notten (2016) is very explicit on this point: she argues poverty measurement issues challenge the identification of the target group and lead to a downward bias in the estimated targeting performance of MISs in six European countries. Her conclusion is that the targeting performance of MIS may be more fruitfully assessed by triangulating information on conceptually different poverty indicators (such as income-based relative poverty and material deprivation[2]) and focusing on the set of households identified as poor by both. Similarly, Gorjón and Villar (2019) claim the target efficiency of the RGI should be evaluated with respect to both the administrative definition of poverty used to select households into treatment and a more standard measure (the income-based Sen's poverty measure) to assess how the administrative poverty concept correlates to the more standard one.

In the present section, we take stock of these insights and propose a novel conceptual framework for assessing the target efficiency of MI schemes that explicitly takes into account the ambiguity surrounding poverty definition and measurement. Most importantly, our framework also provides a useful guide to identifying the possible

[1]Coverage is expressed in terms of potential (eligible) units. The microsimulation approach, which is also used in the present work, allows to simulate the eligibility to the various MISs and compared eligible units to the poor population according to commonly used AROP indicator.

[2]Layte et al. (2000) highlight that the benchmark poverty indicator adopted in the framework of the Irish National Anti-Poverty Strategy (NAPS) is also a combination of an income-based relative poverty measure and an indicator of material deprivation (households must satisfy both requirements to be considered poor). The importance of using non-monetary indicators to understand the living conditions of the poor and capture some of the multidimensional aspects of poverty is stressed by Nolan and Whelan (2010).

reasons behind mistargeting. Its main steps may be summarized as follows:

1. MI schemes are widely recognized as a policy tool to fight poverty and social exclusion;

2. Poverty, however, is an elusive concept that depends on the interplay of many dimensions: every poverty measure has its own limitations and different indicators often disagree on the identification of poverty status;

3. To select eligible units (the *de facto* target), the policymaker thus defines a set of eligibility criteria. The eligibility criteria, which must satisfy some measurability and non-manipulability conditions (Brewer et al. 2017), reflect the policymaker's preferences[3] and implicitly define an 'administrative' poverty concept;

4. The poverty concept implicitly defined by the eligibility criteria may then be compared to other well-established and policy-relevant poverty concepts, which identify the theoretical target of the scheme. The *de facto* target will compare differently to different theoretical targets;

5. Triangulation between the administrative poverty concept and the poverty concept underlying the theoretical target offers interesting opportunities to disentangle poverty measurement issues from design errors (in line with Notten 2016).

A distinctive feature of our framework is thus the identification of a theoretical target group of MISs, given by the households complying with a given policy-relevant or otherwise of interest poverty concept, and a *de facto* target, given by the households complying with the eligibility requirements of the scheme. Since poverty lines and eligibility requirements are often defined over different dimensions of well-being, the theoretical target group and the *de facto* target group often differ. This distinction makes a crucial point: the target efficiency of MISs may be assessed in a strict sense referring to the *de facto* target group, thus evaluating the ability of the policy to reach its administrative goal (what is usually referred to as take-up rate), or in a broader sense referring to some theoretically meaningful poverty concept (the theoretical target group), thus evaluating the ability of the policy to contrast some well-established forms of poverty and social exclusion. In this paper we are most interested to this second case.

Targeting inefficiencies of minimum income schemes may thus stem from three different sources:

1. The limitations of the poverty concept on which the theoretical target group of the MIS is based (i.e., its inability to correctly identify as poor all (and only) the units with a sufficiently low level of well-being);

2. The imperfect overlap between the theoretical and the *de facto* target group of the MIS (eligibility criteria are generally based on different dimensions of well-being than the relevant poverty concept);

[3] An important component of the policymaker's preferences is the expected budgetary amount to be devoted to the scheme.

3. The failure to reach all eligible units, i.e., non-take-up.

Each of these non-mutually exclusive sources of inefficiency generates a conceptually different type of error:

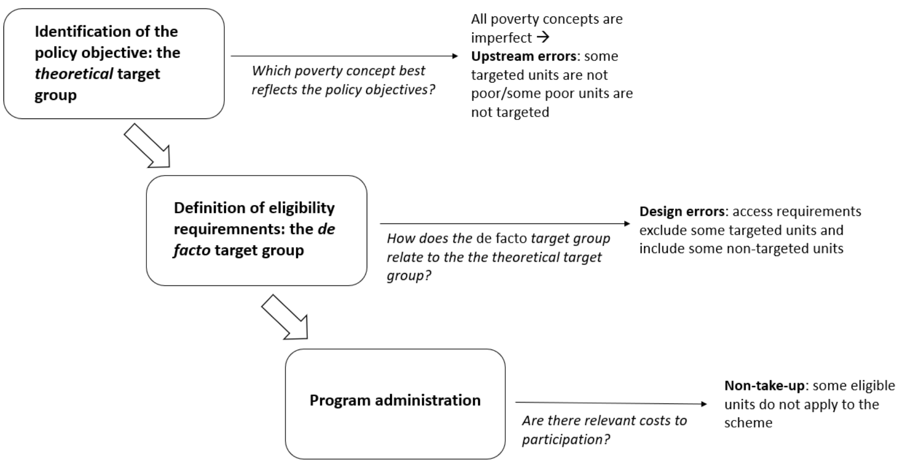
1. *Upstream errors* arise when the poverty concept underlying the theoretical target wrongly represents the effective well-being of poor and non-poor of units. Take for instance consumption-based absolute poverty measures: units classified as poor may have a relatively high level of well-being when the poverty indicator underestimates some relevant welfare dimensions (e.g., frugal preferences). Conversely, units classified as non-poor may have a relatively low level of well-being when the poverty indicator overestimates some relevant welfare dimensions (e.g., quality of in-kind public services or non-utility-related expenses);

2. *Design errors* arise when eligibility requirements relate imperfectly to the theoretical target group. Indeed eligibility requirements may be thought of measurable and non-manipulable proxies of an unobservable concept such as well-being and may thus be defined over dimensions which differ from those relevant for poverty identification (e.g., income-based eligibility requirements and consumption-based poverty). Design errors also arise when the technical assumptions on which eligibility to the scheme is assessed differ from those underlying the relevant poverty threshold (e.g., equivalence scales);

3. *Non-take-up* arises when potentially eligible units do not apply to the MIS. This specific type of error has been extensively studied (Besley 1990, Bargain et al. 2012, Goedemé and Janssens 2020, Nelson and Nieuwenhuis 2021) and has to do with the administration of the program, the economic and psychological costs related to claiming the social benefit, and, possibly to the fear of sanctions in case of income underreporting.

Figure 1 below visualizes the steps above.

Figure 1: Steps in the definition of a means-tested MIS and possible sources of target inefficiency.



We thus define target efficiency in terms of how well the set of effective beneficiaries of the scheme compares to the theoretical target[4]. From an operational point of view, when data on effective beneficiaries are available, we propose the sequential procedure described below and represented in Figure 2:

1. Compute the poverty measure underlying the theoretical target excluding the MI transfer from the relevant resource definition;

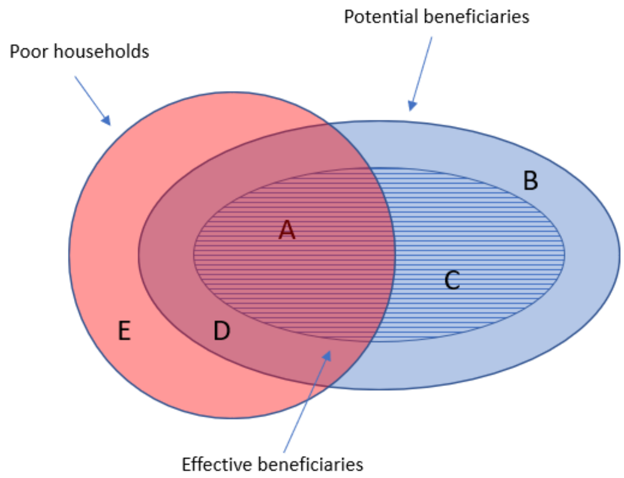
2. Compare the set of effective beneficiaries (the inner circle corresponding to areas A and C) to the theoretical target (the red circle corresponding to areas A, D, and E). This gives the measure of the ability of the MI scheme to effectively target the concept of poverty of interest. It allows computing the coverage rate $\left(\frac{A}{A+B+E}\right)$ and to identify I-and II-type errors: I-type errors – i.e., poor households which do not benefit from the scheme correspond to areas D and E. II-type errors – i.e., non-poor households which benefit from the scheme correspond to area C;

3. Simulate eligibility to the scheme and compare the set of potential beneficiaries (the light blue circle corresponding to areas A, B, C, and D). Non-take-up is given by areas B and D.

The various areas of Figure 2 highlight different aspects of the relation between the given MIS and the benchmark poverty concept. For instance, it may be of interest to distinguish exclusion by design (area E) from non-take-up among the poor (area D) or to analyse poverty measurement issues by investigating the welfare-relevant characteristics of households in areas C (II-type errors) and D (poor households that despite being eligible for the scheme do not claim the benefit). The possibilities for further exploration clearly reach far beyond the above examples.

[4]Our choice to focus on effective beneficiaries is data-driven since our dataset records administrative information on RdC receipt and highlights the effective ability of the RdC scheme to target households in absolute poverty. Of course, focusing instead on potential beneficiaries (as in Figari et al. 2013) would be equally justified.

Figure 2: Effective beneficiaries, potential beneficiaries, and the theoretical target: an illustration.



The conceptual framework we propose is comprehensive and flexible enough to address several issues. On the one hand, when the policy objective of a MI scheme is stated in the general and vague terms of 'fighting poverty', it highlights the fact that evaluating targeting performance against different poverty indicators will yield very different results (in line with Notten 2016). On the other hand, once the theoretical target of interest has been established, our framework recognizes that mistargeting may arise for a number of technical and theoretical reasons (differences in the welfare dimensions considered, territorial differences in thresholds, differences in equivalence scales, different treatment of in-kind income and imputed rents) and that potential flaws in the poverty indicator should also be taken into account. In particular, jointly considering information on poverty status, eligibility to the scheme, and benefit receipt, may provide useful indications on both the target efficiency of the MI scheme and the validity of the poverty indicator: when units are both poor and eligible, we may be relatively sure the poverty indicator is correctly identifying a state of deprivation and, at the same time, the MI scheme is target efficient[5]. When units instead are poor but not eligible (I-type errors) or eligible but not poor (II-type errors) it is worth trying to disentangle the flaws of the poverty indicator from the defects of eligibility criteria by comparing different aspects of well-being. Considering information on effective benefit receipt may be extremely useful in this process. In Section 4below we try to do so in the context of our empirical application.

Before moving on to a more detailed description of the theoretical and technical

[5]While Notten (2016) suggests defining the theoretical target of MI schemes in terms of the union set of an income-based monetary poverty indicator and a non-monetary indicator measuring material deprivation, we suggest exploiting the intersection between the benchmark poverty concept (theoretical target) and the administrative poverty concept implicit in the eligibility requirements to identify the different sources of inefficiency. As a consequence, not all II-type error households should automatically be thought of as 'undeserving'. Our reasoning also complements the intuitions in Headey (2008) and Fisher et al. (2022) who argue poverty, and well-being in general, is better assessed jointly considering different welfare dimensions namely income, consumption, and wealth.

reasons behind design errors, two important questions need to be addressed. Why do different poverty indicators provide different answers on the extent and composition of poverty? And is there a class of poverty indicators that is best suited to be used in the assessment of the target efficiency of MI schemes? These are complex questions and providing complete answers is outside the scope of this paper. Nonetheless, some hints are useful to understand the groundings of our conceptual framework and to motivate our interest in the Italian case.

In general, economic well-being depends on the interplay of different welfare dimensions (mainly income, consumption, and wealth) whose distributions may differ at any point in time. As a consequence, unidimensional poverty indicators defined over different welfare dimensions will necessarily disagree – at least to some extent – on the identification of poverty status. Similarly, different assumptions on the definition of poverty lines will identify different groups of poor people (as is the case for the use of different equivalence scales). In light of these complexities, a large body of literature (Ringen 1988, Headey 2008, Fisher et al. 2015, Fisher et al. 2022) suggests jointly considering different dimensions of well-being may greatly enhance confidence in measured poverty outcomes. However, in the context of unidimensional poverty measurement, well-established theoretical reasons[6] and some empirical findings suggest that consumption-based absolute poverty indicators are closely linked to economic disadvantage (Meyer and Sullivan 2009, Meyer and Sullivan 2011, Meyer and Sullivan 2012 for the US, Brewer et al. 2017 for the UK). This last consideration is extremely relevant to our analysis. Indeed, Italy is the only European country estimating an official consumption-based poverty measure with household-specific thresholds based on reference budgets, so evaluating the target efficiency of the newly established MI scheme (RdC) with respect to this specific theoretical target seems extremely important. Indirectly, as discussed above, our exercise also helps outline some of the possible limitations of the Italian official poverty indicator. Evaluating the target efficiency of RdC with respect to the official absolute poverty indicator is also justified from an institutional perspective: while the legislative decree instituting the RdC (d.l. 4/2019) describes the measure as an active labour market policy and as a tool to fight poverty (not specifying which type of poverty) INPS (the national social security institute) declared in a parliamentary hearing held in March 2019 that RdC should be evaluated also with respect to its ability to reduce absolute poverty and the poverty gap[7].

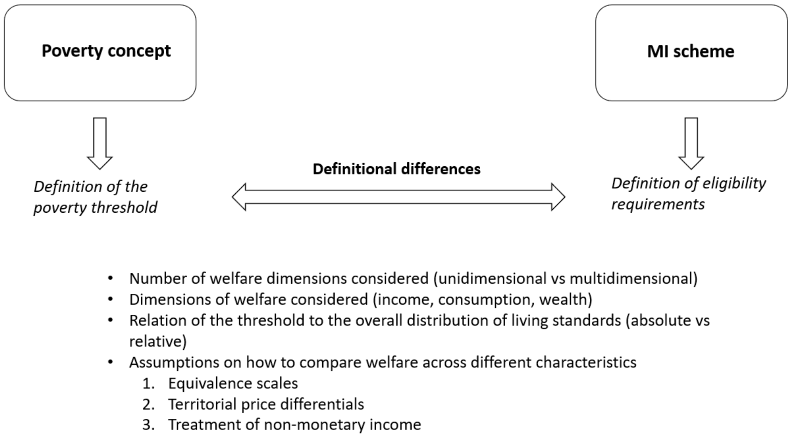
Finally, it is worth complementing our conceptual framework by discussing in greater detail some of the technical and theoretical reasons behind what we called design errors (i.e., the inability of the eligibility requirements to a MI scheme to match the theoretical target group identified by a given poverty indicator). As both MI schemes and poverty measures divide the population into two mutually exclusive groups according to some prespecified threshold, it is easy to see that design errors

[6]In particular households may use accumulated wealth or debt to smooth income fluctuations, income-based poverty measures may wrongly confuse transitory income shocks with permanent differences in well-being. This consideration is especially relevant in cross-sectional data and in line with the intuitions of the life-cycle model (Modigliani and Brumberg 1954) and the permanent income hypothesis (Friedman 1957).

[7]INPS report for the General Director's audition at the XII Commission (public and private work) of the House of Representatives, March 6, 2019.

arise from the different assumptions underlying the definitions of poverty lines and eligibility thresholds.

Figure 3: A detailed description of the reasons behind design errors.



While often dismissed as useless technicalities, these assumptions are extremely relevant to the effective distribution of public benefits and should be carefully taken into account when designing or evaluating a means-tested policy. They may be divided into four main groupings: i) the number of dimensions considered when defining the thresholds (unidimensional vs multidimensional); ii) the different welfare dimensions on which the thresholds are based (income, consumption, wealth); iii) the relation of the threshold to the overall distribution of living standards (absolute vs relative); iv) the assumptions adopted to compare welfare across different characteristics. This last grouping is the most technical and includes the choice of equivalence scales, the treatment of territorial price differentials and the treatment of non-monetary income, such as in-kind welfare benefits and imputed incomes from some types of consumption (e.g. imputed rents for homeowners). Figure 3 above summarizes.

2.1 Minimum income schemes and absolute poverty: the Italian case

The previous section proposed and discussed a novel comprehensive conceptual framework to evaluate the target efficiency of MI schemes with respect to specific poverty measures. In this section we set the stage for our empirical application in two different ways: on the one hand, we describe in detail both the object of our evaluation (the RdC scheme) and the target against which we evaluate its efficiency (the official absolute poverty indicator estimated by ISTAT). On the other hand, we identify the discrepancies in the definitions of poverty and eligibility thresholds that generate *ex-ante* design errors. We are of course well aware of the fact that fighting absolute poverty is not the only objective of the RdC scheme implying design errors may in part be explained by the attempt to balance different (and contrasting) goals. However, since poverty reduction is one of the headline motivations behind the institution of RdC, and the absolute poverty indicator has attracted much of the debate on poverty in Italy since it has been first estimated in 2005, we feel our assumption about the theoretical target is fully justified.

In April 2019, the RdC (passed into law by l. 26/2019 converting d.l. 4/2019) substituted the Reddito di Inclusione (Rei) to become Italy's most important MI scheme. Although the name (Citizenship Income) may suggest a universal and unconditional basic income, article 2 of l. 26/2019 clarifies the RdC is a means-tested cash benefit conditional on participation in job-search activities (Jessoula et al. 2019). Eligible households, indeed, must cumulatively satisfy the wide set of requirements concerning citizenship/residence, income, wealth, and consumption of durable and luxury goods listed below.

For what concerns citizenship/residence, the household member filing the application must be an Italian or EU citizen or have been residing in the country for at least 10 years, the last two of which continuously.

For what concerns income and wealth, the household must cumulatively have:

1. An annual ISEE – a composite indicator taking into account information on income and wealth – lower than 9,360€;

2. An annual equivalised income no higher than 6,000€ (the equivalence scale used will be described below);

3. Real estate assets – excluding the family home – no higher than 30,000€;

4. Other movable and financial assets below a threshold of 6,000€ for the first household member incremented by 2,000€ for every other household member up to a maximum of 10,000€. This threshold is further incremented by 1,000€ for every child starting from the second and by 5000€ for every disabled member.

For what concerns consumption of durable goods household members must not have bought cars or motorcycles in the preceding two years or have any kind of boat at their disposal.

The RdC has been endowed with more budgetary resources and is thus more generous than the Rei. The overall benefit is designed so to have two distinct components (art.3). The income component tops up the difference between annual household equivalised income and the threshold of 6,000€ multiplied by the equivalence scale, which takes a value of 1 for the single-member household and attributes 0.4 to every other adult and 0.2 to every other minor aged up to a maximum of 2.1 (2.2 in presence of disabled members) thus assuming very large economies of scale. The rent/mortgage component compensates rent costs for tenant household up to a maximum level of 3,600€ and the mortgage instalment up to a maximum level of 1,800€.

The duration of the benefit is 18 months, which can be renewed after a 1-month suspension and conditionality requirements for individuals able to work are related to the subscription of a "Work pact" with the Public Employment services, and the acceptance of at least one in three "suitable" job offers (in increasing distance from the place of residence).

As mentioned in the previous paragraph, Italy is a unique country in what concerns poverty measurement: indeed, since 2005 the Italian statistical institute (ISTAT) estimates an absolute consumption-based poverty measure based on the reference budgets approach (Cutillo et al. 2020, ISTAT. et al. 2009). According to this indicator, a household is considered poor if its monthly expenditure – net of some items not directly related to utility and gross of imputed rents – falls short of a household-specific poverty line defined as the monetary value, at current prices, of a basket of basic needs (i.e., reference budget). The key idea is that households spending less than a minimum amount cannot satisfy basic needs and must be considered poor.

The basic needs considered in the reference budget concern adequate nutrition, accommodation, and participation to social life and are assumed to be uniform across the national territory (except for minor differences due to external factors such as weather conditions). However, since the combinations of goods and services required to satisfy this fixed basket of basic needs vary according to the number and age of household members, the geographical area of residence and the type of municipality, the poverty lines also vary according to these dimensions (and are thus household specific). This allows comparing welfare levels across households with different characteristics.

Once the main characteristics of both the object and the target of our evaluation have been pointed out (the RdC scheme and consumption-based absolute poverty respectively), the crucial issue is to determine how they relate. In other words, what may we expect, based on the knowledge of the technical details defining the two concepts, on the overlap between the sets of eligible and poor households[8]? The question is complex since several issues play a role.

First, eligibility to the RdC scheme is assessed by combining information on multiple dimensions of well-being (income, wealth, and ownership of durable goods) and on a residence requirement, while absolute poverty is assessed on the basis of consumption expenditure alone. These differences likely generate some discrepancy between the set of poor and eligible households: for instance, households eligible for the RdC scheme may consume above the poverty line if they draw on the (limited) savings they have or if they receive income from irregular sources (informal labour market, underreported income). From the standpoint of target efficiency evaluation, this would result in a II-type error. On the other hand, non-eligible households could consume below the poverty line if they have some kind of preference for low consumption (especially if they are only marginally above one or more of the eligibility thresholds). From the standpoint of target efficiency evaluation, this would result in a I-type error. This last issue highlights that when poverty/eligibility to a MI scheme is assessed on the basis of some multidimensional indicator (as is the case for the Material Deprivation poverty indicator and for the RdC), it is difficult to assess the welfare situation of households deprived according to some but not all of the welfare dimensions considered. For instance, in the context of our analysis, households which are not eligible for the RdC because of a single welfare dimension (e.g.,

[8]We focus here on eligibility to stress the relation between the poverty concept implicit in the RdC eligibility requirements and consumption-based absolute poverty. The focus of the empirical application is on actual recipients, with eligibility to the scheme simulated in a second stage.

slightly exceeding financial assets) are excluded from the benefit despite an overall very precarious economic condition. Finally, the residence requirement, which has no intrinsic connection to well-being, might exclude from the RdC many otherwise highly deprived households: indeed, 30% of the households that would be eligible for the RdC scheme except for the residence requirement are poor[9]. Overall, we may thus expect rather high discrepancies in the sets of poor and eligible households due to the differences in the welfare dimensions considered.

Second, different assumptions on how to compare welfare levels across different household characteristics may be another source of misalignment between the set of poor and eligible households. More specifically, different assumptions are made about:

1. The economies of scale of living together (i.e., how to compare welfare levels of households of different sizes). While absolute poverty lines increase with household size in relation to the variation of individual needs (which depend on 6 age classes), the RdC equivalence scale is fixed, with coefficients depending only on two age classes, and levels off quite rapidly;

2. The importance of regional price differentials (i.e., how to compare welfare levels of households living in different regions/municipality types). While absolute poverty lines, defined as the cost of a basket of basic needs, explicitly take into account price differentials across geographical areas and municipality types, all RdC eligibility thresholds are unique across the national territory.

The combined effect of these different assumptions may be quantified, though not disentangled, by comparing the RdC equivalence scale and the implicit equivalence scale underlying the absolute poverty lines across the three main geographical areas of the country (North, Centre, South). More specifically, to account for differences in the distribution of characteristics across geographical areas, we use sample weights to compute population averages of RdC equivalence scales and poverty lines. We then compute the implicit equivalence scales underlying the poverty lines dividing the different poverty thresholds by the value of the threshold for a single-member household[10]. The main results are summarized in Figure 4 below.

[9]Similarly, both income and consumption of this group of households tend to be lower (-33% and -63% respectively).

[10]Both the RdC and the absolute poverty equivalence scales are uniform across the national territory but they may differ across geographical areas because of the difference in the distribution of household characteristics: for instance, for what concerns the RdC equivalence scale, if 4-member households have on average more minor-aged children in the south, this implies the value of the sample equivalence scale for 4-member households will be lower in the south because minor aged-members get a 0.2 value while members aged over 18 get a 0.4 value. Similarly, the weighted average of poverty lines allows us to take into account the different distribution of household characteristics across geographical areas. One thing that is very important to remember is that the equivalence scale underlying absolute poverty lines also takes into account price differentials across geographical areas and municipality types (we do not explicitly assess the variation in equivalence scales across municipality types).

Figure 4: Difference in equivalence scales by geographical area of residence.

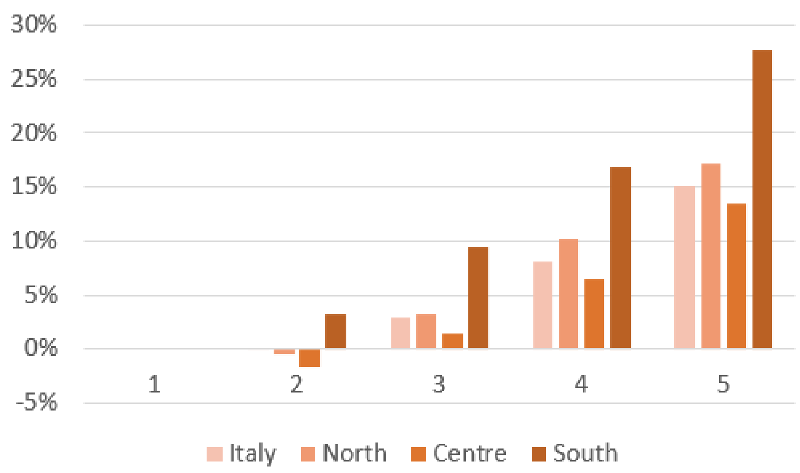


Figure 4 shows the percentage difference between the implicit equivalence scale underlying the absolute poverty lines and the RdC equivalence scale for households up to five members (a positive value indicates a higher value for the implicit absolute poverty equivalence scale). While differences are negligible for small households (1 or 2 members), they become extremely relevant for larger households and in a nonlinear way across geographical areas: RdC equivalence scales tend to overestimate the economies of scale of living together (i.e., to assume lower values as household size increases) and increasingly so in the south.

These differences may have a very important impact in terms of misalignment between eligible and poor households and should not be dismissed as useless technicalities.

3 Data

To accomplish the goals set out in the earlier parts of this paper, we employ a novel dataset for Italy that records detailed survey information on household consumption expenditures and administrative information on labour incomes and social transfers for a representative sample of 42,818 individuals (living in 18,718 households) in 2019.

The dataset was developed using individual fiscal codes to merge (deterministically) the 2019 wave of the Italian Household Budget Survey (HBS)[11] with several administrative archives managed by the Italian National Social Security Institute (INPS) containing information on: i) employment contracts and labour incomes[12]; ii) pensions received (differentiating old-age, survival, disability, and other types of

[11]The HBS is carried out on a yearly basis by the Italian National Institute of Statistics (ISTAT) and records detailed information on household expenditure and individual-level demographic characteristics of its members.

[12]For what concerns labour incomes, we are able to observe the entire career of the surveyed individuals. We chose to retain information since 2015.

pensions); iii) unemployment and furlough benefits for both employees and (a portion of) self-employed; iv) public family allowances; v) Isee declarations (the official indicator of household equivalised income in Italy); vi) RdC receipt.[13] To be consistent, we express all variables in annual terms. The resulting dataset is thus named AD-HBS in light of its combined use of survey-based and administrative data. To the best of our knowledge, no dataset in Italy records simultaneously detailed information on consumption expenditures and various income sources *for the same individuals*[14].

An important strength of the AD-HBS dataset is that information on transfer income (including MI schemes) directly results from the administrative archives of the social security institution managing the various public programmes (including RdC). This has several advantages: first of all, since self-reported transfer income has been often found to be considerably understated in surveys (Meyer and Sullivan 2011), this greatly reduces measurement error for this specific income source which is so important for the less well-off. Second, for what concerns RdC, having information on *actual* beneficiaries allows us to avoid the various assumptions needed to simulate its implementation (e.g., transfer size) and take-up (Bargain et al. 2012, Gallo and Raitano 2019). This last point deserves to be stressed: since we are able to observe the absolute poverty status of the actual RdC recipients, we may focus on the direct link between RdC and poverty status without making any (more or less arbitrary) assumption on how the RdC recipients distribute among the population of eligible households.

Although the information collected into the AD-HBS dataset is very rich, some imputations are nonetheless necessary to simulate the eligibility requirements of the RdC and identify eligible households. In practice, we need to impute Isee values for the large part of the sample (13,080 households out of 18,718) for which they are missing. The main reason for this lack of information relies on the fact that despite the Isee declaration is mandatory to claim most means-tested transfers within the Italian welfare system (e.g., MIS, exemption or reduction of tuition fees, access to homecare support, essential services), many households decide not to file it for several reasons, such as the aversion to red tape bureaucracy, self-exclusion due to high income, fear of tax assessments, and language barriers (Boscolo et al. 2021). To be noted, the share of households with no ISEE declaration is much lower among absolute poor households (41%) with respect to that among non-poor households (72%).

While the Isee declaration is very complicated and made up of several sub-indicators, to our aims we only need to impute four of them: the household income indicator (*Indicatore della Situazione Reddituale* or ISR) and the household wealth indicator (*Indicatore della Situazione Patrimoniale* or ISP) to calculate the ISEE

[13]In the dataset, among MIS benefits, we are able to distinguish between RdC and the Reddito di Inclusione (ReI), the previous national MIS replaced by RdC in April 2019. It follows that some households received both measures in 2019.

[14]Bank of Italy's Survey on Household Income and Wealth (SHIW) collects information on both household incomes and consumptions. However, the information on household expenditures is much more aggregated and relatively less reliable than the one collected by the HBS dataset (Cifaldi and Neri 2013)

value,[15] and the household financial wealth and household property wealth (excluding the main residence) indicators to assess the eligibility to the RdC benefit. Given the high number of zero values (especially in the wealth variables), to impute missing values we adopt a two-stage regression method in the framework of multiple imputation (Rubin 1987, Schenker and Taylor 1996). First, we use a logistic regression imputation method to fill in missing values of the binary variable reporting if a household has a zero income/wealth or not, and then (for those having a non-zero value) we use the predictive mean matching imputation method proposed by Raghunathan et al. (2001) to fill missing values of continuous income/wealth variables. By this method, imputed values are calculated as the mean value of a number of closest observations (or nearest neighbours), which is set to 30 in our estimates.[16] All regression models for imputation count a large set of covariates: the age group, citizenship, education level, and marital status of the household head; household size, presence of underage children, work intensity of household members; tenure status and overall household income (as it results from the administrative records); the degree of urbanization and the NUTS-3 region of residence. All estimates are weighted using household sample weights provided in HBS data. To improve the robustness of our results, our imputed values are calculated as the average of 30 replications of the above procedure.

Some drawbacks of our dataset should also be remarked. First, administrative labour income may be underreported. This could be a serious issue for the self-employed, who may engage in tax avoidance or tax evasion practices much more easily than other categories of workers (Raitano and Fantozzi 2015). Income underreporting, however, may be an issue in surveys as well (Pissarides and Weber 1989). Second, we are not able to observe capital and business incomes, which are not recorded in the archives managed by INPS, thus underestimating the overall income for some households.

3.1 Comparison with total population in terms of RdC receipt

To assess whether our sample is actually representative of the Italian population for what concerns the RdC receipt, we compare weighted-up sample statistics to the population totals for the year 2019 provided by INPS in July 2021[17]. The results of this test, summarized in Figure 9 in the Appendix, show that sample totals match the population ones reasonably well. In particular, the 2019 AD-HBS sample tends to slightly overestimate the number of recipient households and individuals (+10,400 or 0.9% and +121,700 or 4.5% of the population values respectively) and to underestimate the average monthly benefit (-25€or -5.1% of the population value). The fact that our sample overestimates recipient individuals more than recipient households in relative terms means that the share of large households among RdC

[15]The missing ISEE value for the year 2019 is then obtained through the following formula: $ISEE = ISR + 0.2 * ISP$.

[16]The closeness is based on the absolute difference between the linear prediction for the missing value and that for the 'known' values. Of course, therefore, the closest observations are those reporting the smallest differences.

[17]Inps Report July 2021

recipients is slightly overrepresented or, conversely, that the share of single persons is underrepresented. Using data from the April 2019-December 2019 Report of RdC by INPS,[18] we find that this is indeed the case. Finally, while the underestimation of the average monthly benefit, seems to be related to three northern regions only (Lombardia, Trentino-Alto Adige, and Valle d'Aosta), the sample approximates quite well the regional distribution of RdC recipient households. In this case, the greatest misalignment (2.5% overestimation of recipient households) is reported for the region Sicilia. Finally, the aggregated expenditure on the RdC that results from the weighted-up sample figures (3.87 billion €) is very close to the total expenditure estimated by INPS of 3,90 billion €. Overall, we can thus conclude that our representative sample is reasonably well aligned to the population totals concerning access to and generosity of the RdC benefit.

With this discussion in mind, the following section turns to the exploration of the association between the official consumption-based poverty measure and RdC receipt.

4 Absolute poverty and RdC receipt: an empirical assessment

The present section turns to assess the target efficiency of the RdC scheme with respect to the official consumption-based absolute poverty indicator. In section 2 we defined the target efficiency of a minimum income scheme as a measure of "how well" the set effectively targeted units matches the theoretical target.

Our empirical strategy, inspired by the theoretical framework proposed in section 2, is straightforward: first, we compare the set of households effectively receiving the RdC with the set of poor households, thus dividing the population into four mutually exclusive categories according to RdC receipt and poverty status. Second, we analyse the distribution of welfare-relevant household characteristics according to the four identified categories to provide some insights into the mechanisms at work. Third, we explore in greater detail the inefficient areas (I- and II-type errors) also simulating eligibility requirements to disentangle design errors and potential flaws of the benchmark poverty indicator (Section 4.2).

Before proceeding, an important caveat has to be made: as highlighted in section 2, some households may have been lifted from poverty by the additional amount of expenditure made possible by the RdC transfer. As a consequence, to properly assess the association between the two concepts, this (unknown) additional amount of expenditure must be subtracted from the expenditure definition used to measure poverty. Since the institutional arrangements governing the RdC strongly encourage recipient households to spend the cash transfer within the month, we assume an average propensity to consume out of the cash transfer equal to 1[19]. As households

[18] Inps Report January 2020

[19] Many theoretical and empirical studies indeed find that the average (marginal) propensity to consume are inversely related to the income quantile (see for instance Fisher et al. 2020 and many contributions from Keynesian and Post-Keynesian macroeconomics). Since most RdC recipients are in the bottom three income deciles (Gallo and Raitano 2019), we hold our assumption may be justified. To be further noted, if the monthly RdC benefit is not fully spent within the same

are interviewed in the HBS survey in different months over the year and the first RdC benefits have been disbursed starting in April 2019, we make this correction only for those recipient households interviewed after March 2019[20].

The first step of our analysis is summarized in Tables 1 and 2, which illustrate the distribution of households according to RdC receipt and poverty status with sample weights used to refer to population totals. Four mutually exclusive categories are identified: poor and recipient households (i.e., correct targeting cases), poor and not recipient households (i.e., I-type errors), not poor and recipient households (i.e., II-type errors), not poor and not recipient households. The results are very interesting: first, the coverage rate is only 24.9%. In other words, only a quarter of poor households received RdC in 2019 with the large majority excluded from the scheme. Conversely, 2.7% of the non-poor received the RdC. From a different perspective, 41.4% of households receiving the RdC for at least one month in 2019 were poor, while 5.6% of households who did not receive the RdC were poor.

Table 1: Households by RdC receipt and absolute poverty status. Absolute values and relative frequencies.

RdC receipt	**Poverty Status**		**Total**
	Not poor	Poor	
Number of households (thousands)			
Not recipient	23,482	1,395	24,877
Recipient	655	463	1,118
Total	24,137	1,858	25,994
Relative frequencies (%)			
Not recipient	90.3%	5.4%	95.7%
Recipient	2.5%	1.8%	4.3%
Total	92.8%	7.2%	100.0%

Source: elaborations of the author on AD-HBS 2019 data

month, then the residual part is not 'embedded' in the next monthly benefit, and thus it is lost. We believe that this kind of mechanism engenders a propensity to consume the benefit very close to 1.

[20]Figure 10 in the Appendix shows the variations in the poverty rate (in absence of the RdC) and the share of RdC recipients among poor households change according to different assumptions on the average propensity to consume out of the RdC benefit. As expected, the "counterfactual" poverty rate is increasing in the average propensity to consume out of the RdC benefit.

Table 2: Households by RdC receipt and absolute poverty status. Row and column percentages.

RdC receipt	**Poverty Status**	
	Not poor	Poor
Row percentages (RdC receipt)		
Not recipient	94.4%	5.6%
Recipient	58.6%	41.4%
Column percentages (Poverty status)		
Not recipient	97.3%	75.1%
Recipient	2.7%	24.9%

Source: elaborations of the author on AD-HBS 2019 data

The key takeaway is that the RdC matches imperfectly with the official consumption-based poverty concept as also confirmed by two popular synthetic measures of the target efficiency: the coverage rate in terms of actual beneficiaries, as mentioned above, is low (24.9%) and vertical efficiency[21] is 50.7%.

Some degree of heterogeneity between the concepts is to be expected: on the one hand, income is more volatile than consumption so that households with moderate wealth experiencing income drops may be eligible for RdC but still have a total expenditure higher than the poverty threshold (II-type errors). On the other hand, the strictness of eligibility requirements may exclude some of the poor households from the scheme, as for instance, migrants (I-type errors). Also, if households are classified as poor only because of their frugal preferences – an issue that may be particularly relevant for the elderly – they may be not eligible for the scheme.

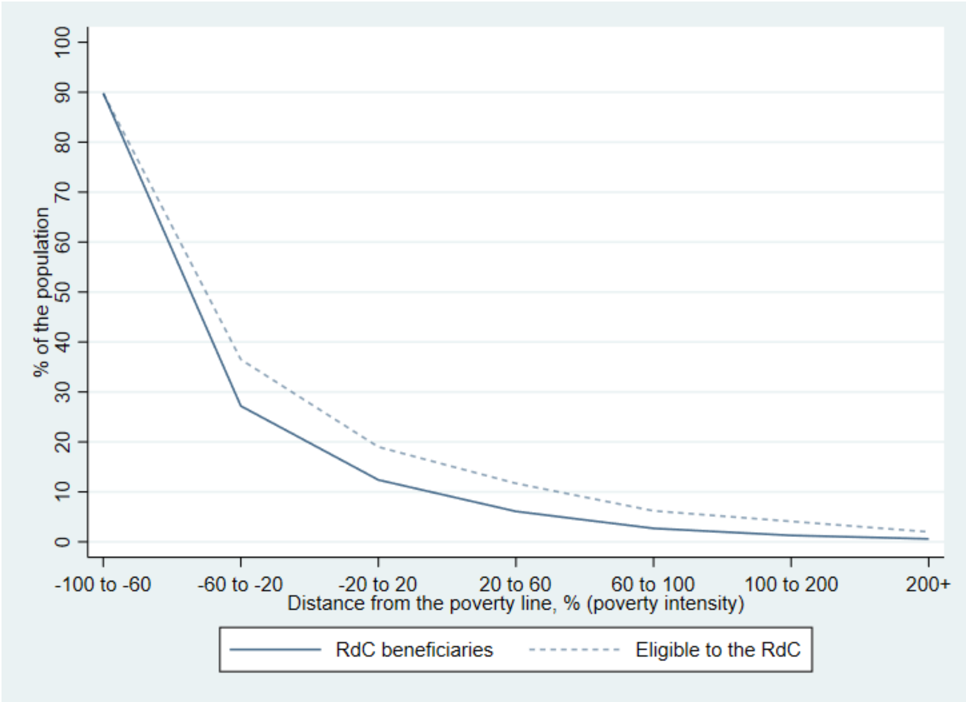
However, it is also interesting to notice that the match between RdC beneficiaries and *income-poor* households, while closer, is also far from perfect: indeed, including imputed rents in the definition of household disposable income and considering the poverty thresholds of the consumption-based measure, only 48.7% of RdC beneficiaries are income-poor (63.1% including households with an income above the poverty threshold but below the RdC income eligibility threshold. On the other hand, excluding imputed rents from the household income definition, these figures increase to 64% and 72.4% respectively, highlighting the crucial role of assumptions on the income definition and the relevance of income mismeasurement in the Isee declarations.

Finally, it is interesting to assess whether the match between RdC beneficiaries and consumption-poor households improves considering a slightly more sophisticated poverty indicator, namely poverty intensity. In other words, is may be extremely relevant from a policy perspective to understand if the likelihood of receiving (or being eligible for) the RdC is at least positively correlated with the distance from the poverty line. The issue is explored in Figure 5 below, where the intensity of poverty has been computed by subtracting the RdC benefit from consumption expenditure for recipient households in line with our previous assumption. While this artificially increases poverty intensity for recipient households, it also allows assess-

[21] The concept of vertical efficiency has been introduced in a seminal paper by Beckerman (1979) and indicates the proportion of benefits accruing those who would have been poor without the benefit.

ing the ‘counterfactual’ degree of poverty intensity in the absence of the RdC. For completeness, the same figure without this assumption is reported in the Appendix (Figure 11).

Figure 5: RdC receipt, eligibility and distance from the poverty line.



Source: elaborations of the author on AD-HBS 2019 data.

Figure 5 shows that the likelihood of being both recipient and eligible is indeed positively associated with poverty intensity (a similar, though less pronounced, pattern emerges from Figure 11.) More specifically, almost 90% of households with an expenditure more than 60% lower than the poverty line receive the RdC (and are thus eligible for the scheme)[22]. Without subtracting the RdC from the expenditure of recipient households this share goes down to 33% (Figure 11). As the gap with the poverty line diminishes, the share of both recipient and eligible households falls and the gap between recipient and eligible households increases (I-type errors up to the point when expenditure is lower than the poverty line). In summary, this (preliminary) evidence points to the fact that while RdC receipt is higher among ‘very poor’ households, more could be done to align this measure to relevant aspects of deprivation.

To dig deeper into the relationship between the Italian MIS and absolute poverty, the following subsections address various issues that may shed some light on the mechanisms leading to I-type and II-type errors. First, Section 4.1 investigates the socio-demographic characteristics which are most common among each of the 4 categories obtained by comparing the sets of poor and recipient households. Section 4.2 then explores some of the possible reasons behind mistargeting with a specific focus on I- and II-type errors.

[22]Arguably, for this ‘extreme’ category results may be biased by the very low sample size.

4.1 RdC and poverty status: main household characteristics

To provide a more complete picture of the mechanisms driving households into the four categories identified above, Table 3 computes odds ratios for a set of welfare-relevant household/household-head characteristics. Odds ratios (OR) are a measure of the association between an outcome (belonging to one of the population categories represented in the columns of Table 3) and an exposure (the characteristics of the household or household head represented in the rows of Table 3) and are calculated as:

$$OR = \frac{Exposed|Outcome}{Exposed|Notoutcome} / \frac{Notexposed|Outcome}{Notexposed|Notoutcome} \tag{1}$$

Values greater than 1 thus indicate a positive association between the exposure and the outcome while values lower than 1 indicate a negative association between the exposure and the outcome – the outcome is independent of the exposure when the odds ratio is equal to 1. Table 3 is completed by the marginal frequencies of the row characteristics among the population (column six) and the group of poor households (column 7). Marginal frequencies sum to 100% within each block of rows.

The results of this exercise are rather interesting and hint to some of the mechanisms at work. It should indeed be clarified that the mechanisms leading to targeting errors are largely independent implying that specific characteristics may be positively associated with both I and II-type errors. To provide an example, take the case of households renting out their home: on the one hand, they could be positively associated with the I-type error category since having to comply with regular (and relevant) payment obligations may induce precautionary savings on the other hand, they could be positively associated with the II-type error category in light of the more generous income-based RdC eligibility requirements. From a policy perspective, it is thus crucial to understand the reasons behind the association between household characteristics and different types of targeting errors so to adapt policy implementation accordingly. Finally, it should be reminded that uncertainty surrounding poverty measurement (upstream errors) calls for some degree of tolerance of targeting errors (especially of the II type).

First, as expected, the education level of the household head[23] is inversely related to both poverty status and RdC receipt. The odds ratios presented in Table 3 certify this pattern: households headed by a low-educated member (at most lower secondary education) are indeed positively associated with all outcomes involving poverty and RdC receipt. The positive association is particularly strong for the poor and recipient category (OR = 4.0) but odds ratios are also high for the poor and not recipient and recipient but not poor categories (2.7 and 2.1 respectively). Symmetrically, households headed by a graduate or by a member with upper secondary education are positively associated only with the not poor-not recipient category (ORs are 5.3 and 1.6 respectively). This pattern identifies an educational cut-off level: upper secondary education appears to be the minimum education level that protects from poverty. Poverty in Italy seems indeed to be strongly related to very low education.

[23]The variable is constructed as the maximum education level of the head or his/her spouse.

Table 3: Household characteristics by poverty 'type': Odds ratios

	Not recipient, poor (I-type)	Recipient, poor	Recipient, not poor (II-type)	Nor recipient, not poor	Share of poor population	Share of total population
Lower secondary education	2.7	4.0	2.1	0.3	69.2%	44.1%
Upper secondary education	0.6	0.5	0.9	1.6	26.2%	37.4%
Tertiary education	0.3	0.1	0.2	5.3	4.7%	18.5%
All local-born	0.2	0.4	0.5	4.4	71.2%	91.1%
At least 1 foreign-born	5.6	2.7	2.0	0.2	28.8%	8.9%
Working age only	0.8	1.2	1.2	1.0	38.2%	40.8%
Adults with children	1.7	2.3	1.5	0.6	35.3%	23.6%
Multigenerational	1.8	1.6	1.6	0.6	1.7%	1.0%
Working age and over 67	0.8	0.3	0.5	1.8	24.9%	34.6%
Work intensity $> 50\%$	0.7	0.2	0.5	1.9	33.1%	45.9%
Work intensity $\leq 50\%$	1.7	2.1	1.3	0.6	25.6%	16.3%
Work intensity $= 0\%$	1.5	7.9	4.5	0.3	20.2%	9.1%
No employable member	0.8	0.4	0.7	1.6	21.1%	28.7%
Homeowners	0.4	0.1	0.2	4.6	42.3%	72.1%
Tenants	2.8	10.3	5.4	0.2	57.7%	28.0%
North	0.9	0.4	0.3	1.8	40.9%	47.8%
Centre	0.6	0.5	1.0	1.4	14.0%	20.5%
South	1.4	3.6	3.3	0.4	45.1%	31.7%
Metropolitan area	0.8	1.6	1.1	1.0	16.1%	16.8%
Medium city	0.8	1.1	1.2	1.0	26.2%	28.1%
Small city	1.3	0.7	0.8	1.0	57.7%	55.1%

Note: All observations are weighted using household sample weights.
Source: elaborations of the author on AD-HBS 2019 data

Second, the presence of foreign-born members significantly increases the likelihood of belonging to the I-type error category – i.e., households not receiving RdC despite being poor (OR = 5.6). This is most probably a consequence of the very stringent residence requirement needed to access the RdC scheme (10 years of residence, the last 2 of which continuously, see Section 2.1). Households with at least one foreign-born member are also positively associated with the correct targeting category (OR = 2.7) and with the II-type error category of households receiving the RdC despite not being poor (OR = 2). While the positive association with the correct targeting category is explained by the overwhelming presence of these households among those in poverty before the RdC transfer (compare columns 6 and 7 of Table 3), the interpretation of the positive association with the II-type error category is more challenging. However, a possible explanation is (latent) income underreporting: indeed, combining self-reported and firm-level information on the activity sector highlights that more than half of the members of households with at least one foreign-born member in the II-type error category work in Construction, Food and accommodation, or Family-related services which are sectors where income underreporting/informal work is likely to be high[24].

Another interesting result that emerges from Table 3 is that presence of children increases the likelihood of both poverty status and RdC receipt. While the positive association is strongest for the poor and recipient category (OR = 2.3) it is also non-negligible for the poor but not recipient and recipient but not poor categories (ORs are 1.7 and 1.5 respectively). In particular, the greater likelihood for this household type not to receive the RdC despite being poor may be explained by the penalizing equivalence scale used to assess eligibility to the RdC scheme (see Section 2.1). Conversely, the presence of members aged 67 or more reduces the likelihood of both poverty status and RdC receipt as highlighted by the odds ratio for the not poor-not recipient category (1.8). To be more specific about this last point, we included in Table 3 multigenerational households (i.e., households with at least 1 minor, 1 working-age adult, and an over 67 member) despite the negligible size compared to the population as a whole (1.0%). What emerges is that, while their likelihood of belonging to each of the four categories is similar to that of non-multigenerational households with children, the presence of members aged 67 or more is often an informal income insurance. Indeed, further elaborations on AD-HBS data highlight that pension income is the primary household income source in about 40% of multigenerational households while it represents less than 10% of total gross household income in only 17% of cases. This result, which deserves further scrutiny, is in line with the argument proposed by Bárcena-Martín et al. (2018) that in Spain multigenerational households are a response to insufficient pro-child targeting of anti-poverty benefits[25].

Work intensity[26] provides further interesting insights into the relation between RdC and poverty status: as expected, households with no employable members (mostly retired people) and households with high work intensity (i.e., greater than 50%), are much more likely to belong to the not poor-not recipient category of correctly non-targeted households (ORs are 1.6 and 1.9 respectively). Conversely, households with low (lower than 50%) and very low (zero) work intensity are strongly associated with membership to the poor and recipient category (the odds ratio is almost 8 for the latter) suggesting the RdC may be particularly good at targeting households with high unemployment[27]. However, it is also interesting to notice that households with low work intensity (both zero and, to a lesser extent, lower than 50%) are also much more likely to be II-type errors. A possible explanation

[24]The precise percentage is 51.27%. The corresponding percentage for households with at least one foreign-born member not belonging to the II-type error category is 34.54%. Overall, self-reported and firm-level information on the ATECO activity sector is available for almost 62% of the members of households with at least one foreign-born. Where firm-level and self-reported information disagrees, we have preferred the former.

[25]Interestingly, Italy and Spain both understood to be "Southern" models of welfare by the seminal contribution of Ferrera (1996) and successive studies on European welfare systems.

[26]Work intensity is here calculated as the ratio between the number of employed and non-retired members aged 16-64 and the total number of members aged 16-64 within the household. An important assumption is that individuals who declare to be employed in the HBS despite having no labour income recorded in the administrative archive are considered not to be employed.

[27]Coverage ratios are and odds ratios are different concepts. To assess whether the RdC is actually good at targeting households with low work intensity coverage ratios are a more appropriate synthetic measure.

for this result is consumption smoothing. Indeed, to the extent that low work intensity results from temporary income drops due to job loss, households may keep consumption at an adequate level by drawing on past savings.

For what concerns tenure status, Table 3 highlights that tenants are in general much more likely to be poor and/or RdC recipients than others. Odds ratios are particularly high for the poor and recipient category (10.3) and for the recipient but not poor category (5.4). This pattern may be partly explained by the fact that RdC eligibility requirements tend to favour tenants (allowing for a higher income threshold). Conversely, homeownership is positively associated with the correctly not targeted group (odds ratio of 1.9).

Finally, living in southern regions is positively associated with both poverty and RdC receipt while the degree of urbanization is in general weakly associated with membership in all four categories. However, the RdC seems to be more effective in correctly targeting poor households living in metropolitan areas.

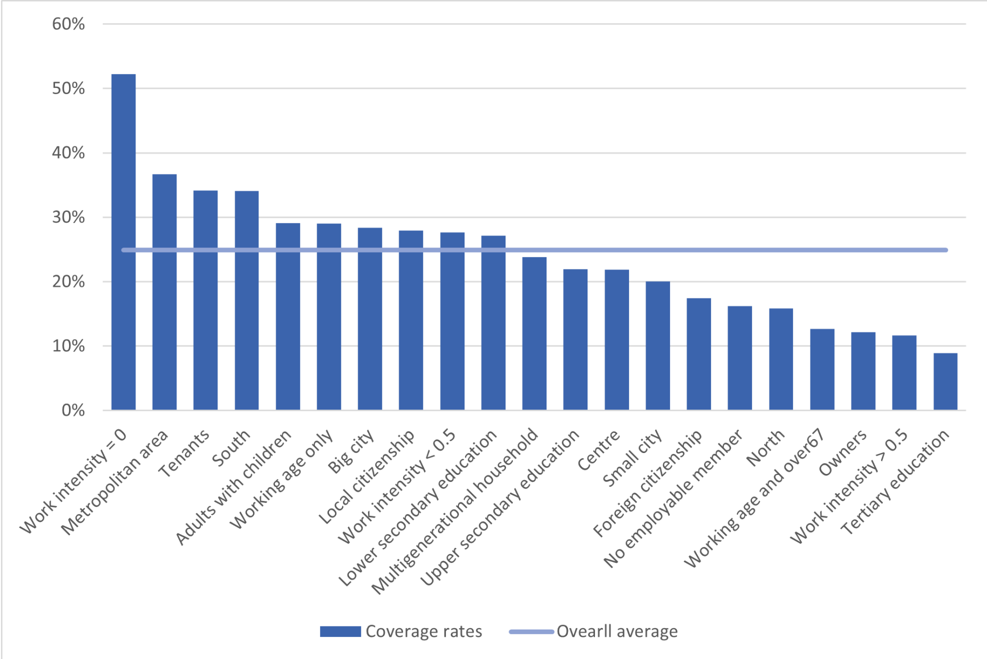
As discussed above, Table 3 highlights that many household characteristics are positively associated with both types of targeting inefficiencies. However, some of the mechanisms discussed above deserve to be highlighted because of their policy relevance: i) the penalization of households with at least one foreign-born member and of large households with children due to the peculiar equivalence scale (both positively associated with the I-type error category; ii) the relatively pro-tenant design of the RdC (which are positively associated with the II-type error category)[28] ; iii) the ability of the RdC to correctly target households with very low work intensity despite a strong positive association with the II-type error category possibly due to consumption smoothing; iv) the greater incidence of I-type errors in small towns, where the application process could be more cumbersome or awareness of the measure could be lower than in large cities. Many of these aspects have been also pointed out by the commission for the evaluation of the RdC at the Ministry of Labour.

The odds ratios presented above are a synthetic measure of the likelihood of belonging to a given population category given various household characteristics. To complete the picture, Figure 6 below shows coverage rates for the same characteristics. Coverage rates assess the ability of the RdC to reach poor households for every given characteristic and thus vary from 0 to 100% (perfect coverage)[29]. In Figure 6 they are sorted in descending order.

[28] It is interesting to notice that the income eligibility requirement for the RdC is **higher** than the absolute poverty line for over 65% of tenant households and 9.2% of homeowners.

[29] Coverage rates in Figure 6 average to 24.9% which is the overall coverage rate discussed in Section 4

Figure 6: Coverage rates by household characteristics.



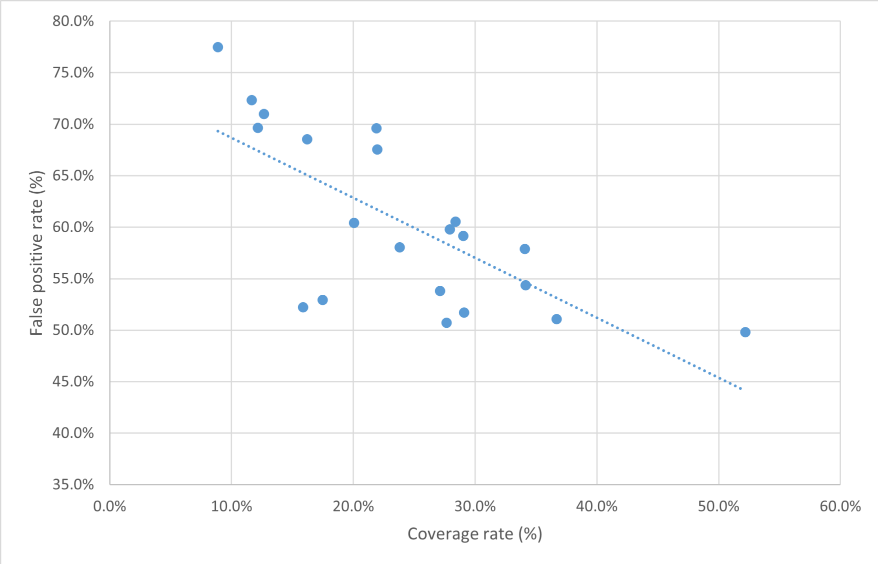
Source: elaborations of the author on AD-HBS 2019 data.

Coverage of the RdC is highest among households with zero work intensity (almost 60%) and also scores above average for households living in metropolitan areas[30] and in the South, tenants, and households with work intensity below 50%. Conversely, coverage of the RdC is lowest among graduates, households with high work intensity, homeowners, and households with retired members. Low coverage among households with retired members may have to do with the inability of the poverty indicator to properly take into account preferences for low consumption of the elderly (which as a consequence, may not feel poor even when classified as poor) while low coverage among households with high work intensity and among homeowners may be due to excessive strictness of the income-based requirement that needs to be satisfied to be eligible for the RdC. Finally, low coverage among graduates may have to do with stigma or non-compliance to the rather stringent wealth-based eligibility requirements of the RdC (see Section 2.1).

Finally, a last interesting aspect is highlighted by the scatter plot represented in Figure 7 below: the coverage ratio is inversely related to what may be called the false positive rate – i.e., the share of II-type error households on total recipients. In other words, the characteristics for which the RdC does relatively well at correctly targeting poor households are also those for which it does relatively well in excluding non-poor households. However, the false positive rate (58.6% on average) is rather high across all characteristics.

[30]Tenants are relatively more frequent in metropolitan areas and low work intensity is relatively more frequent in the South. Clearly, RdC eligibility requirements do not change along the national territory but coverage rates are affected among may other factors by these overlaps. As a consequence, high coverage in the South may be due to low work intensity and high coverage in metropolitan areas to the greater prevalence of tenants.

Figure 7: Coverage rates and false positive rates by household characteristics.



Source: elaborations of the author on AD-HBS 2019 data.

4.2 I-type and II-type errors: a focus

As a final step in the exploration of how the RdC relates to consumption-based absolute poverty, the present section zooms in on the areas of mistargeting – i.e., poor households not receiving the RdC (I-type errors) and non-poor households receiving the RdC (II-type errors) – trying to disentangle flaws in the poverty indicator and design errors.

First, to shed some light on the characteristics associated with mistargeting, Table 4 below shows the results of a multinomial unordered logistic regression of a 3-valued categorical variable that divides the population of households in I-type errors, II-type errors, and correctly targeted/non-targeted cases on the characteristics presented in Table 3 plus a constant. The multinomial logistic regression model estimates how ceteris paribus changes in the covariates (x) affect outcome (y) probabilities $P(y = j|x), j = i, 2, ..., J$ and regression coefficients (not shown) have an interpretation in terms of log-odds ratio. Differently from Table 3, where we used relative frequencies of characteristics to provide some indications on the probability of belonging to a given population category, the multinomial model explicitly estimates (using maximum likelihood) probabilities as:

$$P\left(y = j|x\right) = exp\left(\mathbf{x}\boldsymbol{\beta}_j\right) / \left[1 + \sum_{h=1}^{J} exp\left(\mathbf{x}\boldsymbol{\beta}_h\right)\right], j = 1, \ldots, J \tag{2}$$

In the estimated model the base outcome is assumed be the correct targeting/non-targeting category. Since regression coefficients are difficult to interpret (Wooldridge 2010), Table 4 shows the partial effects of the regressors on the probabilities of each of the three outcomes calculated using an iterative numerical procedure. When regressors are categorical, marginal effects should be interpreted as differences in the probability of the column outcome with respect to the base category (i.e., North for the geographical area of residence).

Table 4: Household characteristics by poverty 'type': Multinomial logit

	I-type	II-type	Correctly targeted/non targeted
Lower secondary (base)			
Upper secondary	-0.047***	-0.011***	0.058***
Tertiary	-0.065***	-0.026***	0.091***
All local-born (base)			
At least 1 foreign-born	0.115***	0.001	-0.0116***
Working age only (base)			
Adults with children	0.021**	0.006	-0.026***
Multigenerational household	0.023	-0.001	-0.022
Working age and over 67	0.000	-0.017***	0.016***
Work intensity $> 50\%$ (base)			
Work intensity $\leq 50\%$	0.015***	0.005*	-0.020***
Work intensity $= 0\%$	0.16**	0.036***	-0.052***
No employable member	0.001	0.016***	-0.017**
Homeowners (base)			
Tenants	0.025***	0.038***	-0.63***
North (base)			
Centre	-0.013***	0.015***	-0.002
South	0.013***	0.027***	-0.040***
Metropolitan area (base)			
Medium city	-0.001	0.004	-0.003
Small city	0.011**	-0.002	-0.009
Observations	18,718		
Pseudo R2	0.138		
Log-likelihood	-7.293e+06		

*** p<0.01, ** p<0.05, * p<0.1

Source: Elaborations of the author on AD-HBS 2017 data.

A few results are worth mentioning. First, in line with the descriptive evidence presented above, the presence of a foreign-born member greatly increases the probability of households belonging to the I-type error category (by 11.5%) as a consequence of the extremely strict residence requirement. However, different from the descriptive evidence, the positive effect of the presence of a foreign member on the probability of the household belonging to the II-type error category is not statistically significant. Second, taking households of only adults as benchmark, the presence of children increases the probability of belonging to the I-type error category by 2.1%, while the presence of members aged 67 or above reduces the probability of the household belonging to the II-type error category by 1.7%. As suggested in Section 4.1, this pattern may be explained on the one hand by the penalizing equivalence scale of the RdC and, on the other hand, by the low frequency of household with old-aged members among recipients (only 18% i.e., almost half of their weight in the overall population). Third, zero work intensity increases the probability of households belonging to both the I-type and the II-type error categories with respect to households with work intensity above 50% (by 1.6 and 3.8% respectively). These results (which are similar to those for low work intensity) are in line with the discussion in Section 4.1: the positive effect on the probability of receiving the RdC despite not being consumption-poor, which is much smaller for households with low work intensity (0.5%), may be due to consumption smoothing (especially since households with high work intensity have more stable income flows) while the positive effect on the probability of not receiving despite being poor may be due to the high frequency of households with zero or low work intensity among the poor. Correspondingly, zero work intensity reduces the probability – with respect to households with work intensity above 50% – of the correct targeting/non-targeting outcome (by 5.2%). This result is explained by the fact that zero work intensity greatly reduces the probability of correct non-targeting[31] and is thus coherent with the high coverage ratio of the RdC among households with zero low intensity (52%[32]).

Finally, high education (upper secondary and tertiary) significantly decreases the probability of the household belonging to both I-type and the I-type error categories (by 4.7 and 1.1% respectively for upper secondary education), while paying rent positively affects it (by 2.5 and 3.8% respectively). The strong positive association between paying rent and belonging to the II-type error category may be due to the pro-tenant institutional arrangements of the RdC.

The stage is now set to finally zoom in on households belonging to the I- and II-type categories: this allows, on the one hand, to discuss some of the possible mechanisms excluding poor households from (I-type errors) and including non-poor households into the scheme (II-type errors) and, on the other hand, to disentangle potential flaws in the consumption-based absolute poverty indicator from design errors.

For what concerns I-type errors we tackle two main issues. First, we distinguish households excluded by design (Figari et al. 2013, Nelson and Nieuwenhuis 2021) from those who, despite being eligible, do not apply to the scheme (non-take-up)[33]. Second, we discuss the role of preferences for low consumption and measurement error in consumption as a mechanism driving part of poor households away from the RdC scheme. To do so, we exploit an HBS variable [34] recording self-perceived economic well-being and build on the idea that when economic means are self-assessed

[31]We show this result in an additional estimated model not shown and available on request. Zero work intensity turns out to increase the probability of correct targeting by around 4% while reducing the probability of correct non-targeting by over 10%.

[32]The coverage ratio among households with zero work intensity reaches 60% if a different

[33]Policy implications are indeed very different in the two cases: exclusion by design issues may be solved changing the eligibility criteria, while improving advertisement and reducing the stigma associated with claiming the measure appear more relevant to address non-take up issues (Notten and Gassmann 2008, Marx et al. 2016).

[34]Perceptions on economic well-being are collected into the HBS survey through a specific question asking households to assess their economic resources in the last 12 months (with respect to household needs) by means of a 4-level Likert scale (i.e., Good, Adequate, Inadequate, Absolutely inadequate). In our analysis, we consider perceived household well-being as high for individuals answering at least 'adequate' to the previous question. The latter group represents 65% of the total sample, but only 33% of the sample of poor households.

as adequate, households may not want to claim a targeted MIS. This mechanism is thus related to the inability of the poverty indicator to correctly account for the preferences of some households.

For what concerns II-type errors, we discuss three sets of issues. First, yearly household expenditure recorded in our dataset may be overstated due to both data-collection and aggregation issues[35]. Second, households who experienced a negative income shock in previous time periods may be smoothing their consumption or taking some time to switch to a lower consumption path. Third, households may comply to eligibility criteria in light of underreported income. We consider yearly expenditure to be potentially overstated for i) households with at least one member working at the time of interview who worked less than 26 weeks in 2019 and/or ii) households who spent over 3000€ on at least one in seven categories of goods and services[36]. In the first case, expenditure overstatement is due to the diary component (households were consuming more in the month of interview due to their higher temporary labour income) while, in the second case, it stems from a composition effect due to the purchase of durable or infrequent goods. Some households may thus be mistakenly classified as not poor because of a measurement error in the variable used to measure poverty, highlighting a flaw in the consumption-based poverty indicator. However, even when not sufficient to shift households out of poverty, expenditure overstatement somewhat lessens concerns about this specific type of targeting error.

Households have been instead assigned to the consumption smoothing group if they simultaneously experienced a household labour income drop larger than 30% from 2018 to 2019 and have a ratio of consumption expenditure to net household income lower than 2 (when the information of the labour income drop is absent use instead the self-reported change in economic conditions). In this case, mistargeting is due to a justified temporary misalignment between the theoretical and the *de facto* target.

Finally, households have been assigned to the income underreporting category if the ratio of consumption to net disposable household income is greater or equal to 1.5 (allowing some overlap with the consumption smoothing category).

Figure 8 shows the main results. First of all, in line with the discussion in Section 2, 90% (1,248,000 out of 1,394,000) of I-type households are not eligible for the scheme: design errors are thus the main reason why poor households are excluded from the benefit. An analysis of the reasons for exclusion by design highlights that the most stringent eligibility requirement is the one on household income, which is not met by 84.2% of I-type errors, followed by the Isee requirement (not met by 55.8%), the movable assets requirement (not met by 53.5%), the residence require-

[35]Households interviewed in the HBS survey are required to fill-in a diary recording all expenditures in a 2-week period and are asked of the total amount spent for single items in the preceding 1, 3, or 12 months. To retrieve monthly average expenditure ISTAT then divides total amounts spent on these items (including durable goods) by 3 or 12 depending on the relevant time span. While this methodology is very good at estimating monthly expenditure of a representative household, it may yield biased results for the expenditures of single households with potential implications for poverty measurement.

[36]Classes of goods and services considered are clothing and footwear, furnishings and household equipment, health expenses, durable goods referring to transport, recreation, restaurants and accommodation and other goods and services.

ment (not met by 26.5%) and the real estate assets requirement (not met by 1.9%)[37]. On the other hand, no household is excluded by the requirement on durables' consumption. Zooming in on households excluded by *a single* requirement confirms that most households are excluded only because of the income requirement (56.6%). Interestingly, the second most relevant cause of exclusion for these households is the residence requirement (25.1%) highlighting once again this 'unfair' feature of the RdC. However, it should also be pointed out that non-take-up plays an important residual role: 10.5% of I-type error households are indeed potentially eligible for the scheme. Of these households, 29% (42,000 out of 146,000 households) did not present an ISEE declaration despite self-assessing their economic situation as inadequate (potentially signalling unawareness of the existence of RdC or fear to apply due to sanctions/conditionalities), and 7% did not present an ISEE declaration but self-assessed their economic situation as adequate. The remaining 64% (94,000 households) did not claim the RdC benefit despite presenting an ISEE declaration possibly due to stigma, aversion to conditionality or adequacy of self-perceived living standards.

Figure 8: Classification of I-type (left panel) and II-type error (right panel) households.

Notes: Volume of circles is not representative of the weight (in terms of observations) of the specific category in the observed subsample. Percentages sum up to 100% within each panel except for rounding errors. All observations are weighted using household sample weights. Source: elaborations of the author on AD-HBS 2019 data.

These results also provide interesting insights into the potential flaws of the consumption-based absolute poverty indicator. Indeed, 25% (340,000 out of 1,394,000) of poor households not receiving the RdC self-assess their economic conditions as adequate and do not present an ISEE declaration, somehow validating their self-perceptions. Assessing the relationship between the official poverty measure ('objective poverty') and self-assessed adequacy of economic means ('subjective poverty') is

[37]Income is also found to be the most stringent eligibility requirement by the commission for the evaluation of the RdC.

beyond the scope of this paper, also in light of the well-known endogeneity of perceptions with respect to material conditions (Milanovic and Jovanovic 1999; Ravallion 2012; Ayllón and Fusco 2017).

However, the co-presence of high self-perceived well-being, lack of interest in welfare programmes and low consumption may be an indication of preferences for low consumption and/or measurement error in consumption expenditure (downward bias). Further elaborations on AD-HBS data provide some support for both these hypotheses: on the one hand, households reporting a high perceived economic well-being and not presenting and ISEE declaration have on average i) higher equivalised (using the standard OECD scale) disposable incomes than those reporting a low perceived well-being and presenting an ISEE declaration (the whole income distribution is shifted to the right) and ii) more members aged 67 or above (28% vs 6.5%). Higher disposable income suggests low consumption may be a choice rather than an imposition while larger presence members aged 67 may indicate prioritization of needs not captured by the consumption-based absolute poverty indicator. On the other hand, almost 95% of these households have a food expenditure which is below the food component of the poverty threshold (something that is difficult to justify alongside high perceived well-being) pointing to a possible downward bias in measured consumption expenditure[38]. This result highlights that cross-sectional microdata on consumption expenditure may in some cases provide a wrong representation of household well-being, and, as a consequence, consumption-based poverty figures must be interpreted with some caution.

Results for II-type error households are shown in the right panel of Figure 8. As argued above, mistargeting concerns are less relevant for the 13% of households in the consumption smoothing and/or overstated expenditure category but outside the income underreporting category (86,000 out of 655,000). More specifically, overstatement of yearly expenditure (which globally concerns just over one-fifth of II-type error households) questions, from an opposite perspective with respect to the previous case of downward measurement error, the use of survey-based consumption data for poverty measurement. Estimating the impact of these measurement issues on poverty outcomes is an interesting line for future research. However, almost one-half of II-type households are assigned to the income underreporting category (307,000 out of 655,000) with 214,000 not simultaneously belonging to the consumption smoothing and/or the overstated expenditure categories. Two issues are worth stressing: on the one hand, the size of this category is at least to some extent inflated by the income information missing from our dataset, mainly capital and business incomes and, crucially, incomes from informal work; on the other hand, of the 214,000 households belonging only to the income underreporting category, almost one fifth spend only up to 25% more than the poverty threshold thus showing a rather low living standard and lowering concerns about target inefficiency of the RdC[39]. On the

[38]Absolute monthly values for food expenditure are indeed extremely low: 86€for one-member households, 159€for two-member households, 214€for three-member households, up to 229€for 4 or more member households

[39]The gap with the poverty line has been computed disregarding the RdC benefit, to be consistent with previous elaborations. While 'artificially' pushing down the expenditure of recipient households (reducing the positive distance with the poverty line), this assumption allows to grasp their potential standard of living without the benefit.

contrary, the roughly 170,000 households remaining, are clearly the most concerning for the target efficiency of the RdC.

As a final caveat, classifications in Figure 8 are necessarily affected by arbitrary assumptions. As a consequence, the ensuing discussion should be interpreted as a first step in the understanding of the mechanisms driving I- and II-type errors to be expanded in future analyses.

4.3 Extensions

We are planning to extend the above provisional draft in various directions, with a specific focus on empirical elaborations.

First, the relationship between consumption-based absolute poverty, income-based absolute poverty, and RdC receipt should be better explored. Although section 4 provides some initial insights into the relationship between the set of RdC recipients and the set of households whose income falls short of the absolute poverty threshold, further elaborations may provide a deeper understanding of the mechanisms driving mistargeting. For instance, it would be interesting to assess whether the characteristics associated with I- and II-type errors change when measuring poverty according to consumption, income or both.

Second, the analysis of targeting errors may be expanded in several ways: i) Figure 8 could be complemented by a detailed breakdown of household characteristics within each subgroup thus shedding additional light on the relevance of flaws in the poverty indicator and design errors; ii) the variables, concepts and methodologies adopted to identify the different overlapping subgroups among I- and II-type errors may be further refined: for instance, the very high rate of exclusion by design among I-type errors should be tested in the subsample of households who presented an Isee declaration in 2019 to rule out the role of the assumptions used to impute the Isee indicator where missing. For what concerns the analysis of II-type errors, potential overestimation of monthly expenditure should consider 'calendar effects' i.e., specific months in which expenditure tends to be higher than usual - such as December. Additionally, the interaction between RdC policy design and poverty lines should be more closely taken into account since it may be the case that income access requirements are higher than the household-specific poverty line, and a more comprehensive definition of consumption smoothing should be provided.

Finally, considerations on poverty intensity as a measure of targeting inefficiency should be more deeply explored, thus complementing the preliminary insights provided by Figure 5.

5 Conclusions

MISs are means-tested monetary transfers targeted to the poor, but multiple definitions of poverty exist and the same scheme may relate differently to different poverty concepts. In the first part of this paper, we thus proposed a novel theoretical framework to assess the target efficiency of MISs that takes this specific issue into consideration (Section 2). Our framework identifies three types of target inefficiencies (upstream errors, design errors and non-take-up) and suggests using all available information the disentangle them. More specifically, design errors are identified comparing the share of poor households according to the benchmark poverty concept not eligible for the scheme, while non-take-up is obtained comparing actual and potential beneficiaries of the scheme. Upstream errors, which are potentially related to flaws in the benchmark poverty indicator, are instead identified analysing the characteristics of I-and II-type error households.

In the second part of this paper, we evaluated the target efficiency of the recently introduced Italian MIS (RdC) with respect to Italy's official consumption-based absolute poverty indicator. Italy is an extremely interesting case study since consumption-based absolute poverty indicators have been found to be more closely related to severe economic hardship than commonly used income-based relative indicators. Our empirical strategy included three main steps, each one identifying some relevant aspect of the relation between the RdC and absolute poverty.

First, we divided the population if four mutually-excluding categories according to RdC receipt and poverty status. We found the coverage rate among the poor to be on average 25% with three-quarters of poor households excluded from the scheme.

Second, we computed odds ratios to investigate the household characteristics associated with the probability of belonging to each of the four categories. We found (very) low work intensity to be strongly associated with the correct targeting category and presence of children and foreign-born members with the I-type error category. Paying rent is associated with both the correct targeting and the II-type error categories, while low education of the household head and living in the South are positively associated with both mistargeting categories.

Finally, we zoomed in on I-and II-type error households to disentangle design errors from potential flaws in the benchmark poverty indicator: we found that almost one-quarter of poor households not receiving the RdC self-declare an adequate level of well-being and do not apply to any welfare transfer suggesting the consumption-based poverty indicator may not be able to correctly assess their welfare. In this respect, we argue both preferences for low consumption could play a role and measurement error in consumption expenditure may play a role; conversely, while around one-fifth of not poor households receiving the RdC have a potentially overstated yearly expenditure questioning, from another perspective, the ability of survey-based expenditure microdata to correctly assess consumption-based poverty, almost half of the households in this category are likely to have an underreported income (due to tax avoidance, missing information or informal work).

Taken together these results highlight two main areas of target inefficiency of the RdC. On the one hand, excessive strictness of eligibility requirements excludes a large portion of needy households from the scheme (especially large households with children and households headed by foreigners). On the other hand, some households receive the benefit despite having a relatively high consumption and may be thus underreporting their income. Crucially for what concerns policy implications, the former inefficiency is numerically much larger than the latter: almost 750,000 poor households are not eligible for the RdC and have a poor self-assessed economic condition, while around 170,000 households receive the benefit despite consuming well above the poverty line and potentially underreporting their incomes.

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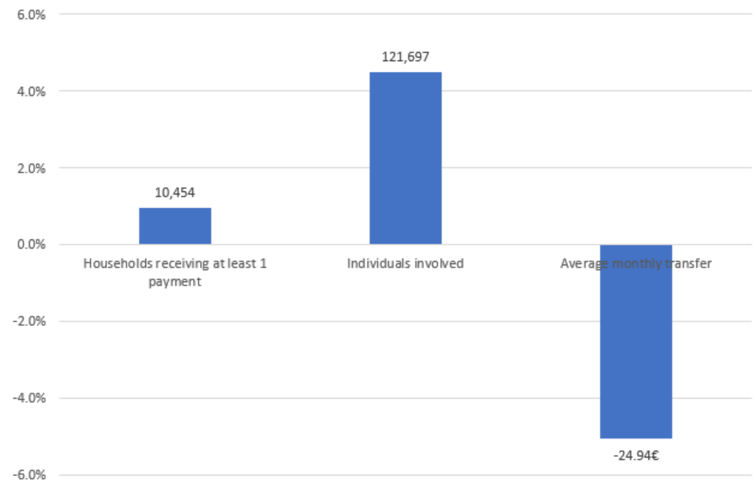
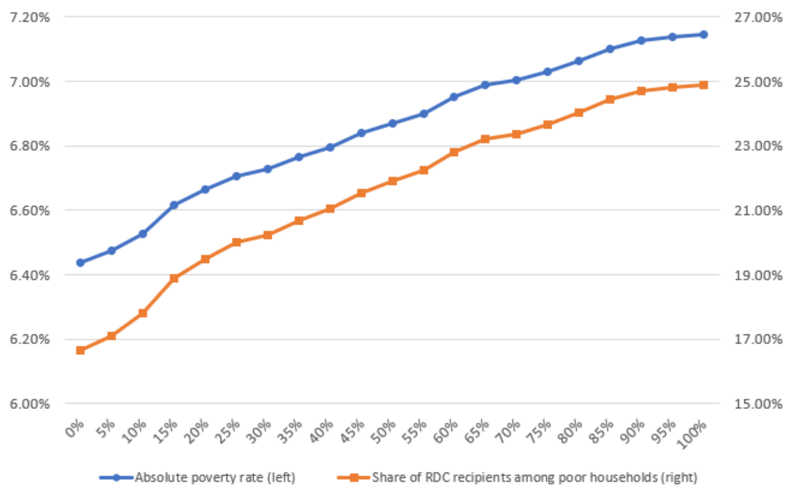
6 Appendix

Figure 9: AD-HBS 2019 and aggregate official statistics, comparison.



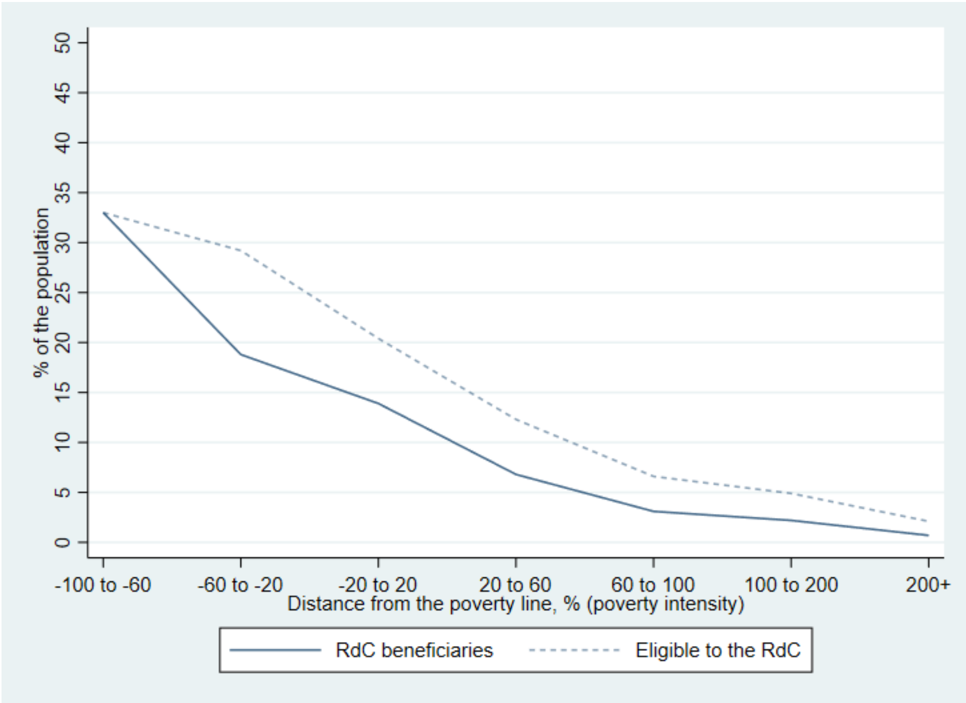
Source: elaborations of the author on AD-HBS 2019 data.

Figure 10: Absolute poverty and share of RdC Recipients among the poor, different assumptions of consumption out of RdC.



Source: elaborations of the author on AD-HBS 2019 data.

Figure 11: RdC receipt, eligibility and distance from the poverty line (no correction for RdC recipients).



Source: elaborations of the author on AD-HBS 2019 data.