Do the Most Vulnerable Know About Income Support Policies? The Case of the Italian *Reddito d’Inclusione* (Rel)

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Abstract
In order to alleviate enduring poverty rates, most European Union (EU) member states have developed policies against poverty since the 1980s. The effect of these policies is, however, undermined by low take-up rates amongst potential beneficiaries. Whilst studies on non-take-up have highlighted a series of explanations as to the reasons why potential beneficiaries do or do not apply for income support, few studies have investigated people’s awareness of the existence of such measures. Yet, knowing about the measure is the first step towards applying for social benefits. Relying on INAPP’s PLUS 2018–Participation, Labour, Unemployment Survey—a unique source of data for income support policies, we seek to assess the determinants of awareness of income support policies. We find that the most vulnerable groups are also those less aware of the measures designed to alleviate their situation.

Keywords Income support · Cash transfer · Vulnerability · Knowledge · Information asymmetry

JEL Classification D04 · D60 · I30

1 Introduction

Despite relative high-income levels, European Union (EU) member states are facing enduring poverty rates. In 2016, Eurostat estimated that about one person in four was at risk of poverty or social exclusion; that is, about 118 million people across the EU (Eurostat 2018: 26). In order to alleviate the phenomenon, most member states have developed policies against poverty since the 1980s. Today’s policies are most often made up of an economic benefit—aimed at providing immediate relief on lower
income households—and a series of social services intended to favour labour market reinsertion (Lødemel e Trickey 2000; Hemerijck 2013), in line with the guidelines established by the European Commission in 2008 (Clegg 2016). The effect of these policies is, however, undermined by low take-up rates amongst potential beneficiaries (Daigneau et al. 2012). Hernanz et al. (2004) estimate that non-take-up rates, that is the ratio of those not receiving the benefit to which they are entitled, in OECD countries vary between 20 and 60%. Whilst studies on non-take-up have highlighted a series of explanations as to the reasons why potential beneficiaries do or do not apply for income support (van Oorschott 1998; Craig 1991; Hernanz et al. 2004; Currie 2004; Warin 2010; Matsaganis et al. 2010; Herd et al. 2013; Van Mechelen and Janssens 2017; Vinck et al 2019), few studies—and none regarding the Italian case—have looked into people’s awareness as to the existence of such measures. Yet, knowing about the measure is the first step towards applying for social benefits.

Whereas most EU member states have had income support policies in place for decades (European Parliament 2017), Italy has only recently joined the ranks with its first nation-wide, structural income policy, the Reddito di Inclusione (ReI; Inclusion Income),1 introduced at the end of 2017. Access to the measure was conditional on the evaluation of family and economic criteria, at least for the first six months of implementation. Starting from 1 July 2018, family requirements were repealed, making access to the measure conditional on economic requirements only, thus giving it a universal character.2 The ReI consisted of economic support3 for 18 months (renewable for 12 more months) and a personalized program of social and work inclusion services. In March 2019 the ReI converged in the Reddito di Cittadinanza (RdC).4 In May 2020, in order to support the people in emergency state due to the economic consequences of the Covid-19 pandemic and excluded by the RdC, the policy maker introduced an emergency income support measure (REM).5 The current economic crisis and the open debate about the validity of RdC to properly address the poorest (Gallo and Raitano 2020) are pushing towards redesigning the public policies aimed at the poverty eradication in Italy.

1 This does not mean that there have never been any income support policies in Italy, at national or local level. As a matter of fact, Madama et al. (2013) show that about 60% of Italian municipalities had some kind of income support policy in the 1990s. Likewise, the ReI was preceded by the Sostegno di Inclusione Attiva (SIA; Active Inclusion Support).

2 A family could benefit from the measure if there was a minor, a person with disabilities, a pregnant woman, or an over 55 person in an unemployed state. According to the economic criteria, which remained unchanged during the year, a family could receive the ReI if it had an ISEE (Equivalent Economic Situation Indicator) not exceeding €6,000, an ISRE (the income component of the ISEE) not exceeding €3,000, real estate assets (other than the dwelling house) not exceeding 20,000 euros and movable assets not exceeding 10,000 euros.

3 The economic benefit is calculated on the basis of an equivalence scale. The maximum monthly benefit are equal to 187 euro per person, 461 euro for a 4 members family and 539 euro for a 6 or more members family. For more info, please, see https://www.lavoro.gov.it/temi-e-priorita/poverta-ed-esclusione-sociale/focus-on/Reddito-di-Inclusione-ReIPagine/default.aspx.

4 The RdC integrates income support with activation measures, aimed at introducing people to the job market. Moreover, it targets a wider audience of beneficiaries. For more info, please, see: https://www.inps.it/prestazioni-servizi/reddito-di-cittadinanza-e-pensione-di-cittadinanza

5 For more info, please, see: https://www.inps.it/prestazioni-servizi/reddito-di-emergenzahttps://www.inps.it/nuovoportaleinps/default.aspx?itemid=53736
Because of its recent introduction, the ReI offers a unique opportunity to look at information asymmetry between different population groups who have a high probability of being beneficiaries as they belong to different dimensions of vulnerability. Relying on PLUS 2018—Participation, Labour, Unemployment Survey—a unique source of data for income support policies, we seek to assess the determinants of awareness to income support policies. About a year after the inception of the first ever income support policy in Italy, only 36.6% of the respondents knew Italy had an income support scheme, of whom only 47.1% knew its name. Do the most vulnerable know about the policies designed for them? This is the research question we aim at answering.

This article investigates people’s awareness of the measure in accordance with their social and individual characteristics; with attention to their vulnerability (here understood as their predisposition to poverty). Under ideal circumstances and considering that the ReI is primarily a policy intended to fight poverty, those who are in need of income support would know about the measure. Our findings point in the other directions, thus suggesting the need for targeted outreach campaigns. To investigate people’s awareness of the measure in relation with their potential need for income support, we draw from the specialized literature and delineate a series of dimensions to capture vulnerability. Said dimensions are: economic situation, work status, education level, gender and geographic location.

This article is organised as follows. In the second section, we propose a selective review of the literature on users’ awareness to policies and vulnerability. In so doing, we refine the purposes and contribution of this study. We then present our data and method in a third section. The fourth section presents the empirical results: first, it heeds the lack of consensus on the concept of vulnerability and identifies the social groups prone to poverty in Italy and, therefore, most in need of income support (additional elements are also presented in the online appendix); then, it intends to answer our research question, whether those in need of income support actually know about the policies designed for them. In line with the findings presented for other countries, we find that the most vulnerable groups of people do not know about the policy. We discuss our results in a fifth section and conclude with policy implications in a sixth.

2 Literature Review

The capacity of income support policies to meet their goals is highly dependent on potential users accessing to the subsidy (Daigneault et al. 2012). A growing number of scholars has focused on the determinants of non-take-up (see inter alia van Oorschott 1998; Craig 1991; Hernanz et al. 2004; Currie 2004; Warin 2010; Matsaganis et al. 2010; Herd et al. 2013; Van Mechelen and Janssens 2017; Vinck et al 2019). Warin (2010) identified three broad groups of reasons for non-take-up: (i) non-knowledge: the eligible individuals are not aware of the program’s existence; (ii) non-demand: individuals choose not to apply; and (iii) non-reception: eligible individuals apply for the program but do not receive the benefit. Whilst it is not relevant, for the scope of this paper, to analyse the reasons why people that apply do not receive the benefit
(third group), we are interested in the reasons why people do not apply at all (first and second group).

The determinants of the “non-demand” group of reasons for non-take-up of means-tested programs can be mainly related to learning, psychological and compliance costs (Herd et al. 2013). The information costs, as well as the time and effort required for understanding the procedures, belong to the first category. Indeed, acquiring information on its rules can be too costly to be worth it. Among the psychological costs, participation in such programs may stigmatize their beneficiaries. Finally, the compliance costs are mainly related to the burden of administrative rules and requirements.

In our paper, we mainly focus on the “non knowledge” group of reasons, that scholars consider the first cause for non-take-up. Van Oorschot’s (1998) dynamic model of benefit receipt considers benefit awareness as part of the first threshold. Through in-depth qualitative methods, Daigneault and Macé (2019) shed light on the experiences of welfare clients and ex-clients in Québec and found that the first driver of non-take-up is the absence of knowledge. They also underline the importance of program promotion, information campaigns and enrolment via community-based organizations. Thus, they conclude that public authorities should actively inform potential participants of the existence of the program through various means (in-person meetings, phone calls, etc.). Figlio et al. (2015), found that strong social networks are associated with program awareness. For instance, when eligibility rules were changed the presence of dense social networks mitigate the effect of confusion and prevent declines in Medicaid take-up rates among Hispanics. Unless enrolment is automatic, individuals who are unaware of a program’s existence will not apply for it (Vinck et al. 2019). Awareness is a crucial aspect of every such policy insofar as income support schemes are intended for vulnerable groups, which also happen to be the less informed ones (Kalogeropoulos and Nielsen 2018). However, lack of knowledge about income support measures is a common phenomenon, even in countries that have had such policies for a long time. For instance, France has adopted minimum income guarantee measures with the creation of the RMI in 1988 (Minimum Insertion Income). Notwithstanding, in a report published in 2011, the French National Committee for the Evaluation of the Active Solidarity Income (RSA for the French acronym, which substituted the RMI in 2009) found that lack or absence of knowledge about the measure is one of the main explanations for non-take-up. Based on a survey on potential beneficiaries, the report shows that 11% of them did not know about the measure whilst 44% admitted knowing little about it (CNERSA 2011: 54). Similarly, the Netherlands implemented its first minimum income guarantee back in 1963, a measure that has changed over the years (Vanderborght 2004). A survey on the general population conducted in 2005 revealed that 29% of the respondents had never heard of the benefit whilst 64% of them had heard of it but knew little about it (Eurofund 2015). Scholars pointed out that non-take up is lower where the claiming process is more automatic (Matsaganis et al. 2010), the program and form are simplified, marketing and branding of policies are improved, as well as the outreach strategies (Herd et al. 2013).

Whilst many studies have focused on awareness of social policies, to the best of our knowledge, none have focused on Italy and, above all, there is no study analysing the information asymmetry about income support scheme among different vulnerable
social groups; yet this is a decisive aspect of any such policy, and one that we address
in this paper.

Empirical evidence available thus far suggests that those who would know of the
measure are not necessarily those in need of income support. Recent studies have
already established that social inequalities are associated with different patterns of
information consumption and selective exposure (Prior 2005; Lindell 2018). As a
practitioner commenting on Italian youth unemployment policy put it: “the policy
instruments in place (…) do not reach potential beneficiaries because, for instance,
you do not have access to information due to the digital divide or they simply live in
environments in which the information does not circulate” (InGenere 2015).6 Research
has shown that difficulties in accessing information and digital divide are more likely
to affect vulnerable groups such as women (Gargallo-Castel et al. 2010), low-income
households (Servon and Nelson 2001; Gonzales 2016), the elderly ICT ageing users,
markets and technologies. European Commission (2010), to name but a few cate-
gories (see also Haight et al. 2014). Corroborating, policy reports have shown how not
knowing about the measure affects its potential outcomes (CNERSA 2011; EuroFund
2015).

As much as poverty and social exclusion, vulnerability is a multifaceted phe-
nomenon. Accordingly, it has been defined in different ways, both across and within
academic disciplines (Alwang et al. 2001). For the purpose of this article, our working
definition of vulnerability lies with the probability of loss of welfare below socially
acceptable norms,7 the fragile integration into the traditional systems of resource distri-
bution and social protection (Maestripieri 2015). A starting point to grasp the concept
is the economic situation of individuals and households. Following Sen (1975; but
see also Dasgupta 2000), income and participation in the labour market are funda-
mental barriers against poverty and exclusion.8 On the one hand, income facilitates
access to commodity bundles and allows the satisfaction of basic needs such as board
and lodging but also health and education. On the other hand, employment is also a
source of recognition and social legitimation. Conversely, lack of employment may
be tantamount to be denied one’s productive role in society.

Unemployment and poverty may vary over time and place, but some social groups
appear to be more vulnerable to economic cycles and crises than others (Saraceno
2015; Simona-Moussa and Ravazzini 2019). Namely, evidence points at larger effects
of economic downturns on the low-skilled, low-educated, young, and elderly (Muriel
and Sibieta 2009; Hoynes et al. 2012; Addabbo et al. 2012). The specialised literature
has also emphasised the vulnerability of women and single parents. Women were
shown to be at a higher risk of poverty for decades now (Ruspini 1998). Because their
role is constructed as that of caregivers with a weaker attachment to the labour market,
they are more likely to do unpaid work, have part-time contract or work in the informal
economy (Ranci 2010; Gornick and Boeri 2017). Single parents, too, present higher
risk-of-poverty rates (Chzhen and Bradshaw 2012), notably because of the difficulties

6 For ease of reading, the excerpt was translated in English and shortened. The reader interested in reading
the entire passage in original language will find the link in the list of references.
7 This definition is inspired from the comprehensive analysis carried out in Alwang et al. (2001: 4).
8 Note that, despite their importance, they do not constitute absolute protection, as bears witness the figures
of in-work poverty (see Halleröd et al. 2015; Ahrendt et al. 2017).
they face to access paid work given the costs of childcare; particularly so for female single parents (Taylor-Gooby 2004). With regard to Italy, evidence shows that, in addition to the groups mentioned above, the risk of poverty is also higher in the south of the country than it is in the north (Billi and Scotti 2019). Likewise, research has demonstrated a differentiated distribution of inequality between core and periphery: remote rural areas are more concerned with poverty than metropolitan areas, which benefit from more dynamic labour markets (Gallo and Pagliacci 2019). What is more, the condition of Italian women appears more severe than in other OECD countries. If female single parents are greatly exposed to the risk of poverty (Simonazzi and Pavoni 2014), poverty and exclusion extends beyond this category to females at large; even more so for part-time and temporary female workers (Mastropieri 2015).

3 Data and Methods

The findings presented in this article are based on PLUS data (Participation, Labour, Unemployment Survey) and its additional module (hereinafter PLUSam) on income support policy. Data collection for both databases was commissioned by INAPP, the Italian national institute for public policy analysis, and carried out in October 2018. The PLUS database is a large set of questions posed to a representative sample of 45,000 people between 18 and 75 years-old residing in Italy. PLUSam is a more specific and narrower set of questions asked to a representative sample of 5,012 respondents, 1,159 of whom intersect with the PLUS database and thus constitute a third database with fewer observations but a larger set of questions (hereinafter PLUS*PLUSam). All three samples were used in this study for different purposes. PLUS was mostly used for descriptive statistics whilst PLUSam and its subset, PLUS*PLUSam, were used to estimate the determinants of policy awareness. In order to produce inferences with the latter two, we adjusted sampling error with the calculation of post-stratification weights, inspiring our method from that used for the European Social Survey (ESS 2014). Namely, we replicated the Universe’s characteristics as to the distribution of age groups, gender, education and macro-region of residence. However, instead of using a cross-classification for gender, age and education (the vector approach; that used for the ESS), we opted for variable-per-variable calibration in order to reduce the risk of having too few observations in some of the cross-classification categories, which could result in inaccurate weights. Descriptive statistics and more information about the dataset are available in the online appendix.

In order to identify the possible candidates for income support policies we first identify the most vulnerable profiles through the use of two proxies for economic hardship or vulnerability: the necessity for a household to postpone medical care (Addabbo et al. 2012); and its inability to face unexpected expenses. In order to determine the profiles with the highest probability of falling in these categories, we run a logistic regression model (for the first indicator) and an ordered logistic regression model (for the second one). In accordance with the specialised literature outlined in the previous section, we tested the following predictors: area of residence, education, work status, gender, type of household (interacted with gender), age, number of people living in the household and size of the city of residence. For these models (model a
and model b), the dependent variable on medical care is binary (1 being postponing care) whereas that on unexpected expenses is ordinal.\footnote{The question posed was: How much an unexpected expense could you face with your own resources? The answers, in order, are: none; less than €300; between €300 and €800; between €800 and €2,000; more than €2,000.}

\[
\text{Logit (Postpone medical care)} / \text{Ordered Logit (Face unexpected expenses)}_i = \alpha_i + \beta_1 \text{Location}_i + \beta_2 \text{Education}_i + \beta_3 \text{Work status}_i + \beta_4 \text{Gender}_i \\
+ \beta_5 \text{Household type}_i + \beta_6 \text{Household type} \times \text{gender}_i \\
+ \beta_7 \text{Age}_i + \beta_8 \text{N. of people in HH}_i + \beta_9 \text{City size}_i + \epsilon_i.
\]

As for testing whether the most vulnerable know about income support policies, we run a series of probit regressions following the basic model (hereinafter model 1):

\[
\text{Probit (Knowing)}_i = \alpha_i + \beta_1 \text{Location}_i + \beta_2 \text{Education}_i \\
+ \beta_3 \text{Work status}_i + \beta_4 \text{Gender}_i + \beta_5 \text{Age}_i^2 + \beta_6 \text{City size}_i + \epsilon_i.
\]

Our dependent variable is a dummy taking value “1” if the respondent knows about the policy and “0” otherwise.\footnote{People who responded, “I Don’t know” have been aggregated in the latter category.} Our predictors correspond to the characteristics that we previously tested to identify the profile of vulnerability. Following the tenet that gender differences are not adequately captured using simple additive dummy variables (D’Ippoliti 2011), models 2 and 3 (Table 2) and models 8 and 9 (Table 3) split the sample into two, according to respondents’ gender. Moreover, in order to control for our respondents’ economic status and types of household, which are missing in PLUSam, we test our basic model described above (model 1 in Table 2) onto PLUS*PLUSam which offers more information about the respondents (model 1’ in Table 3). The models below therefore add: the type of household (model 4); the respondents’ ability to face unexpected expenses, as a dummy taking value “1” if the respondent can afford an unexpected expense of more than 300 euro and “0” if he cannot afford any kind of unexpected expense (model 6); and the necessity of the household to postpone medical care (model 7).

\[
\text{Probit (Knowing)}_i = \alpha_i + \beta_1 \text{Location}_i + \beta_2 \text{Education}_i \\
+ \beta_3 \text{Work status}_i + \beta_4 \text{Gender}_i + \beta_5 \text{Age}_i + \beta_6 \text{Household type}_i \\
+ \beta_7 \text{Household type} \times \text{gender}_i + \beta_8 \text{City size}_i \\
+ \beta_9 \text{Unexpected expenses}_i + \text{Postpone medical care}_i + \epsilon_i.
\]

Finally, we include the interaction terms\footnote{Since the coefficients are average marginal effects, interaction terms are not reported.} between the type of household and gender (model 5, 6 and 7), in order to test whether “single” and “single parent” types
of household have a different probability of knowing about the measure when the family is headed by women or by men.\textsuperscript{12}

\section*{4 Empirical Results}

\subsection*{4.1 Context Analysis: Who are Those Most in Need of Income Support?}

If income support policies are intended to alleviate the immediate economic condition of their beneficiaries, identifying the most vulnerable profiles is a sensible undertaking. In this section we show the main results of our logistic regressions. Only the most relevant results are reported here whilst additional information and figures are presented in the online appendix.

Table 1 below reports the results of both the logistic models, presented in Sect. 3, aiming at defining the most vulnerable categories according to the probabilities of falling into two different kinds of economic hardship: the necessity to postpone medical care (model a) and the inability of facing unexpected expenses (model b). The probability of being vulnerable according to both our indicators\textsuperscript{13} increases if the respondents are female, if they belong to a larger family, if they reside in southern or central areas of Italy compared to being from the northern regions; surprisingly, it increases for people residing in larger cities compared to those residing in small villages and, finally, it increases for unemployed and inactive compared to occupied. Looking at the working status, for retired and students we find opposite results according to our two vulnerability proxies: while as, being retired or students compared to those that are occupied, decreases the probabilities to postpone medical care it also decreases the chance of being able to afford unexpected expenses. We also find opposite results when we look at the age of respondents: while as, being older increases the probability to postpone medical care, it also increases the chance of being able to afford unexpected expenses. The probability of falling in a vulnerable state decreases for people with a higher education and for people belonging to any household type compared to single people. This result is not confirmed for couples, especially those with children, if we interact the household type with being female (in model b), moreover, in model a, we find that being a female single parent increases the probability of postponing medical care (only significant at the 85\% level), thus of being vulnerable, compared to single respondent.

Overall, our analysis shows that there exists a significant difference between men and women when it comes to postponing medical care; more so for single parents with child(ren) (see Figure A4 in online appendix). Further deepening the categories single and single parents with children who are either employed, unemployed or inactive, Figs. 1 and 2 unveil the differentiated probabilities of postponing medical care

\textsuperscript{12} In our gender analysis we mainly focus on single and single parent type of household because they can be distinguished in women or men headed. For the other household types the dataset does not allow to have a gender definition of the household, we only know if the respondent is a man or a woman.

\textsuperscript{13} To allow a correct interpretation of the table 1, we remind that in model b the dependent variable will take higher value if the respondent can afford unexpected expense, so if he/she is not vulnerable. Therefore, the models ‘results have to be read in different way.
Table 1 Logistic regressions results—Based on PLUS dataset

| Model a | Model b | Model b |
|---------|---------|---------|
| Gender (Female) | 0.3696 *** (0.105) | -0.5940 *** (0.075) | |
| Family size | 0.1038 *** (0.024) | -0.0413 *** (0.016) | |
| Age | 0.0060 *** (0.002) | 0.0074 *** (0.001) | |
| Comune size | 0.0519 *** (0.013) | -0.0207 * (0.009) | |
| Area of residence with respect to north | | | |
| Centre | 0.2735 *** (0.046) | -0.3665 *** (0.031) | |
| South | 0.8666 *** (0.040) | -0.7373 *** (0.027) | |
| Education with respect to compulsory and middle school | | | |
| High School | -0.4382 *** (0.040) | 0.7795 *** (0.029) | |
| University | -0.9711 *** (0.040) | 0.7795 *** (0.033) | |
| Work status with respect to occupied | | | |
| Unemployed | 0.7698 *** (0.051) | -1.1088 *** (0.036) | |
| Retired | -0.3271 *** (0.056) | -0.0749 * (0.041) | |
| Inactive | 0.2290 *** (0.054) | -0.7574 *** (0.040) | |
| Student | -0.5306 *** (0.095) | -0.5917 *** (0.048) | |
| Respondent and family type with respect to single household | | | |
| Couple with children | -0.2638 ** (0.113) | 0.4057 *** (0.079) | |
| Couple without children | -0.3988 *** (0.105) | 0.4015 *** (0.073) | |
| Single parent | -0.2695 (0.198) | 0.1956 + (0.130) | |
| Child of couple with children | -0.8436 *** (0.132) | 0.3267 *** (0.084) | |
| Child of couple without children | -0.3230 ** (0.152) | 0.0125 (0.101) | |
| Other | -0.3133 * (0.175) | 0.2318 ** (0.110) | |
| Female*household type with respect to female*single household type | | | |
| Couple with children | 0.0952 (0.119) | -0.2297 *** (0.085) | |
| Couple without children | 0.0364 (0.131) | -0.1578 * (0.092) | |
| Single parent | 0.3563 + (0.221) | 0.1011 (0.148) | |
| Child of couple with children | 0.1909 (0.146) | -0.0701 (0.090) | |
| Child of couple without children | -0.1085 (0.198) | -0.3513 *** (0.129) | |
| Other | 0.0860 (0.206) | 0.0154 (0.134) | |
| Constant | -2.0360 *** (0.147) | | |
| Cutoff 1_cons | | -1.6592 *** (0.103) | |
| Cutoff 2_cons | | -0.3571 *** (0.102) | |
| Cutoff 3_cons | | 0.6348 *** (0.102) | |
| Cutoff 4_cons | | 1.4715 *** (0.103) | |
| N | 45000 | 45000 | |

Source: authors’ elaboration on PLUS dataset

*p value < 0.15  * p value < 0.10  **p value < 0.05  *** p value < 0.01 (robust standard errors in parentheses)
Predictive Margins of gender with 95% CIs

Fig. 1 Probability for employed, unemployed and inactive single men and women of postponing medical care, according to their macro-area of residence (proportions). Based on Model a—Table 1—PLUS dataset according to education levels and macro-area of residence (for couples with children and couples without children see Figure A2 and Figure A3 in the online Appendix). Overall, the less educated, unemployed and residing in the south of Italy, are more likely to postpone medical care (almost 80% for women in single parents’ family type). On the contrary, being from northern regions of Italy, having the highest education level and being occupied gives the lowest probability of postponing medical care (which is less than 10% for men in single-parent family type). Note that all the figures show that there is a difference between genders (the continuous line, representing women is always higher than the dashed line, representing men); one that is more accentuated where households consist of single parents with children (Fig. 2) or of couples with children (see Figure A2 in the online Appendix). In fact, for these two types of households, the distance between the lines, representing women and men, is higher than for singles (Fig. 1) and couples without children types of households (Figure A3).

If we point our attention to the ability to face unexpected expenses, there is a significant difference between men and women with women being more likely to be unable to face unexpected expenses (with a 25% probability versus a 15% probability for men; see Figure A5 in online appendix). Residing in southern regions is also associated with a higher probability of not being able to face unexpected expenses (22% compared to 12.5% in the north; see Figure A6 in the online appendix). Considering education levels, the less educated are less likely to be able to cover unexpected
expenses, with a probability of 22% whereas the most educated are more likely to cover expenses greater than €2,000 (41%; see Figure A5 in the online appendix).

4.2 Do the Most Vulnerable Know About the Measures Designed to Alleviate Their Situation?

In this section, we report the average marginal effects of the 3 probit regressions run on the PLUSam dataset (Table 2) and the 7 more models run on the subset of 1159—PLUS*PLUSam—(Table 3). In model 1, residing in the southern area of Italy, compared to residing in the north, decreases the probability of knowing about the policy by 5.7 percentage points (p.p.). Considering females only (model 2), residing in the south as well as in the centre of Italy decreases the probability of knowing about the measure by respectively 8 and 5.6 p.p.. Higher education levels appear to be associated with higher levels of awareness about the policy: a university degree, compared to compulsory school, increases the chances of knowing about the measure by 44 p.p.. Education seems to have a greater effect for male as the likelihood of knowing about the measure is always higher for males than it is for females, with a difference of at least 9 p.p. when we look at high school. The likelihood increases until 15 p.p. for middle school and university. Moreover, being male increases the probability of being aware of the income support policy by 3 p.p.. When we analyse working statuses, inactive and pensioners are less likely to know of the policy than
Table 2 Average marginal effects—models tested on PLUSam

|                          | Model (1)       | Model (2)—female only | Model (3)—male only |
|--------------------------|-----------------|-----------------------|---------------------|
| Gender (male)            | 0.0306 *        | (0.013)               |                     |
| Age                      | 0.0022 ***      | (0.001)               | 0.0011 (0.001)      |
| City size                | -0.0009         | (0.005)               | -0.0035 (0.007)     |
| Education with respect to compulsory school |                 |                       |                     |
| Middle School            | 0.1732 ***      | (0.019)               | 0.1019 *** (0.026)  |
| High School              | 0.2586 ***      | (0.021)               | 0.2205 *** (0.030)  |
| University               | 0.4361 ***      | (0.026)               | 0.3686 *** (0.038)  |
| Location with respect to North |               |                       |                     |
| Centre                   | -0.0198         | (0.017)               | -0.0563 * (0.024)   |
| South                    | 0.0567 ***      | (0.015)               | 0.08 *** (0.021)    |
| Work status with respect to Occupied |               |                       |                     |
| Unemployed               | -0.0131         | (0.020)               | 0.0013 (0.029)      |
| Retired                  | -0.1015 ***     | (0.028)               | -0.0711 (0.042)     |
| Inactive                 | -0.0814 ***     | (0.019)               | -0.0778 ** (0.024)  |
| Student                  | 0.0014          | (0.033)               | -0.0194 (0.044)     |
| N                        | 5012            | 2831                  | 2181                |

Source: authors’ elaboration on PLUSam data

p value < 0.15 * p value < 0.10 ** p value < 0.05 *** p value < 0.01 (robust standard errors in parentheses)

employed people (by around 8 p.p.). This is especially true for inactive women (model 2) and retired men (model 3). Age also appears to have an effect with being older slightly increasing the likelihood of knowing.

With the purpose of including three important variables in our models, i.e. household types, ability to face unexpected expenses and postponing medical care, we use a subsample intersecting PLUS and PLUSam. In so doing, the number of observations drops to 1159 (see the section on data and method for more on this point). Table 3 below reports 7 models. The results confirm the main findings presented above as to the effect of education, working status and gender (in model 5, 6 and 7 when we insert the new variables in our model). That being stated, decreasing the number of observations increases the standard errors and confidence intervals. Consequently, some variables lose in statistical significance; notably the area of residence and gender (model 1’ and 4). However, looking at the predicted probability by gender, area of residence and education (Fig. 3), the probability of knowing about the policy varies significantly. In the best scenario: being male, with the highest level of education and residing in the northern regions translates into higher likelihood of knowing about the policy (63.4%); being male, with the highest level of education but residing in the southern regions slightly decreases this likelihood (57.1%). In the worst scenario:

14 The household type: the dummy on the ability to face unexpected expense and the dummy on the necessity of the household to postpone medical care.
### Table 3: Average marginal effects – models tested on subset PLUS*PLUSam

|                              | Model (1') | Model (4) | Model (5) - gender*HH type | Model (6) - gender*HH | Model (7) - gender*HH | Model (8) - female only | Model (9) - male only |
|------------------------------|------------|-----------|-----------------------------|-----------------------|-----------------------|------------------------|------------------------|
| **Location with respect to North** |            |           |                             |                       |                       |                        |                        |
| Centre                       | -0.0910    | -0.0886   | -0.0841                     | -0.0748               | -0.0821               | -0.0739                | -0.0512                |
|                              | (0.067)    | (0.064)   | (0.062)                     | (0.062)               | (0.062)               | (0.071)                | (0.106)                |
| South                        | 0.0118     | 0.0198    | 0.0207                      | 0.0404                | 0.0276                | -0.0070                | 0.0931                 |
|                              | (0.063)    | (0.063)   | (0.063)                     | (0.063)               | (0.063)               | (0.082)                | (0.092)                |
| City size                    | 0.0174     | 0.0168    | 0.0165                      | 0.0161                | 0.0173                | 0.0221                 | 0.0123                 |
|                              | (0.021)    | (0.021)   | (0.021)                     | (0.021)               | (0.021)               | (0.026)                | (0.029)                |
| **Education with respect to compulsory and middle school** |            |           |                             |                       |                       |                        |                        |
| High School                  | 0.198 ***  | 0.2026 ***| 0.2255 ***                  | 0.2161 ***            | 0.2226 ***            | 0.1526 *              | 0.2751 ***            |
|                              | (0.059)    | (0.059)   | (0.058)                     | (0.059)               | (0.059)               | (0.087)                | (0.075)                |
| University                   | 0.2436 *** | 0.2528 ***| 0.2736 ***                  | 0.2492 ***            | 0.2685 ***            | 0.22 ***               | 0.2882 ***            |
|                              | (0.064)    | (0.065)   | (0.065)                     | (0.064)               | (0.098)               | (0.089)                |                        |
| **Work status with respect to Occupied** |            |           |                             |                       |                       |                        |                        |
| Unemployed                   | 0.0113     | 0.0121    | 0.0029                      | 0.0298                | 0.0105                | 0.0166                 | 0.0908                 |
|                              | (0.081)    | (0.081)   | (0.081)                     | (0.081)               | (0.079)               | (0.091)                | (0.121)                |
| Retired                      | -0.106     | -0.1342   | -0.0988                     | -0.053                | -0.1029               | -0.0221                |                        |
|                              | (0.163)    | (0.158)   | (0.160)                     | (0.157)               | (0.159)               |                        |                        |
| Inactive                     | -0.1429 *  | -0.1426 * | -0.1086                     | -0.0962               | -0.1070               | -0.0483                |                        |
|                              | (0.083)    | (0.082)   | (0.080)                     | (0.079)               | (0.101)               |                        |                        |
| Student                      | -0.0031    | -0.0106   | -0.0176                     | -0.0145               | -0.0124               | -0.0199                | 0.0362                 |
|                              | (0.062)    | (0.064)   | (0.061)                     | (0.063)               | (0.060)               |                        |                        |
| Age                          | 0.0024     | 0.0023    | -0.0008                     | -0.0007               | -0.0007               | 0.0040                 | -0.0078                |
|                              | (0.063)    | (0.060)   | (0.060)                     | (0.063)               | (0.063)               |                        |                        |
| Gender (male)                | 0.0697     | 0.0642    | 0.1163 *                    | 0.1040 +              | 0.1172 *              |                        |                        |
|                              | (0.063)    | (0.064)   | (0.065)                     | (0.065)               | (0.063)               |                        |                        |
| **Respondent and family type with respect to single household** |            |           |                             |                       |                       |                        |                        |
| Couple with children         | 0.0021     | -0.1489 * | -0.1486 *                   | -0.1513 *             | -0.4741 ***           | 0.2484 **              |                        |
|                              | (0.132)    | (0.108)   | (0.108)                     | (0.108)               | (0.134)               |                        |                        |
| Couple without children      | 0.0141     | -0.1307   | -0.1142                     | -0.1123               | -0.4802 ***           | 0.2860 **              |                        |
|                              | (0.152)    | (0.107)   | (0.107)                     | (0.104)               | (0.186)               |                        |                        |
| Single parent                | 0.3276 *   | 0.1443    | 0.1508                      | 0.1460                | -0.5497 *             | 0.7003 ***             |                        |
|                              | (0.199)    | (0.106)   | (0.106)                     | (0.105)               | (0.202)               |                        |                        |
| Child of couple with children| -0.0202    | -0.2134 **| -0.2020 **                  | -0.2155 ***           | -0.4662 ***           | 0.0923                 |                        |
|                              | (0.130)    | (0.084)   | (0.084)                     | (0.083)               | (0.131)               |                        |                        |
| Child of Single parent       | 0.0580     | -0.1273   | -0.1127                     | -0.1284               | -0.4569 ***           | 0.2835 **              |                        |
|                              | (0.158)    | (0.119)   | (0.119)                     | (0.118)               | (0.175)               |                        |                        |
| Other                        | 0.0908     | -0.2891 **| -0.2977 **                  | -0.2997 **            | -0.4398 **            | -0.3236 **             |                        |
|                              | (0.181)    | (0.123)   | (0.123)                     | (0.123)               | (0.220)               |                        |                        |
| Unexpected expense (more than 300 euros) | 0.0931 *   |          |                            | 0.0050                | 0.2044 **             |                        |                        |
|                              | (0.056)    | (0.067)   | (0.065)                     |                        |                        |                        |                        |
| Postponed medical care       | -0.0461    |          |                            |                       |                       |                        |                        |

Source: authors’ elaboration on PLUS*PLUSam data  
Notes: + p value < 0.15 * p value < 0.10 ** p value < 0.05 *** p value < 0.01 (standard errors in parentheses)
being female, with the lowest level of education and residing in the northern regions gives a 15.9% probability of knowing about the policy; being female, with the lowest level of education but residing in the southern regions gives the worst likelihood of knowing (12.2%).

In Model 5, we introduce the type of household among the variables, and we interact it with the gender, in order to control the different effect of a female/male headed household. In particular, as we have already stressed, from a gender point of view, the analysis is only most relevant for households composed of a single person or a single parent. In fact, only in these two types of household we can assign a “gender type” to the family, which are made of only one head of the family. In Fig. 4 we show the probability of knowing about the measure by gender, type of household and education. There appears to be a clear difference between men and women who are single or single parents. Single women, with the highest level of education, have the highest probability of knowing about the measure (more than 93.3%). For single parents, we find the opposite results. These findings are confirmed in model 7 and 8, where we split the sample in two subsamples for males and females. Looking at couples with and without children the likelihood of knowing is much lower than in single families (while as, it is not detectable the difference between men and women in the “couple” household type). However, despite the type of family and gender, the likelihood of being aware of the policy always increases with the education level (especially so for men).
Finally, the less vulnerable (as proxied by the ability to face unexpected expenses greater than €300) have more chances of knowing about the policy: 9 p.p. (model 6). The vulnerability proxy is not statistically significant for women (model 8) while it is for men (model 9), thus confirming the differentiated awareness according to gender found in model 5. More specifically, our models always confirm that women are less likely to know about the policy, especially when they have children (or they are part of a family), regardless of their levels of vulnerability. Differently, postponing medical care is never significant (model 7). This may be related to the fact that the likelihood of needing medical care increases with age, and so does the likelihood of postponing medical care in situations of vulnerability. Indeed, this proxy may be less able to capture vulnerability at all levels, but it may be more suitable for the elderly. Accordingly, the ability to cover unexpected expenses is more suitable a proxy for vulnerability inasmuch as it covers a wider spectrum of situations.

5 Discussion

The findings presented above show that vulnerable groups are less aware of the policies designed for them than people who are better off. More specifically, the analysis of vulnerability conducted on PLUS data shows that the not employed (unemployed, inactive), women, especially when single mother (but not consistently in our results),
the less educated, people residing in southern regions, the young and people living in larger families are the most fragile category. Among these categories the less educated, the inactive, women, people residing in southern region and the most economic vulnerable are also those less aware of the existence of the ReI. Some of our results point out that single mothers, or women that are part of a family, are less aware of the policy compared to single women, we find the opposite for their male counterpart. The stronger information asymmetry of women may be driven by a weaker social network of reference (Figlio et al. 2015) mainly because of their role constructed as that of caregivers with a weaker attachment to the labour market (Ranci 2010; Gornick and Boeri 2017). Moreover, research has shown that difficulties in accessing information and digital divide are more likely to affect vulnerable groups such as women (Gargallo-Castel et al. 2010). Knowing about the policy also increases with age. It is interesting to note here that, in spite of this result, young adults and children are experiencing a sharper increase in the rate of poverty if we compare them to elders in Italy (Gallo and Luppi, 2019). Moreover, it is interesting to stress that the unemployed are not among those who are less aware of the ReI. However, part of them may receive unemployment benefits and, thus, may not need or be eligible to other income support measures. One explanation could lie with the fact that people in search of a job may be informed about the ReI through the employment centres or other social services. Conversely, the inactive are further away from the social services’ reach and may thus be less likely informed about the policy. Not knowing may also result from the composition of the social networks in which the most vulnerable are inserted (see inter alia Figlio et al. 2015; InGenere 2015). Further research is needed to test this hypothesis.

Our work presents some limitations that this section aims at pointing out. Firstly, PLUS contains data for individuals within households without allowing the distinction between respondents and other members of their household. Therefore, comparing men and women implies that we focus on males and females who are single and single parents (as opposed to couples), thus neglecting the condition of vulnerability of married women who would be poor if they were on their own (Goldberg2009). That being said, an analysis by headship subgroups remains important for the purpose of income support policies (Klasen et al. 2015).

Overall, this article provides evidence of the lack of knowledge of a policy on the part of its target group. There is here only one step from lack of knowledge to low take-up rates,¹⁵ and just another one from low take-up rates to undermined effectiveness of income support policies. If this paper is not able to reconstruct the chain of reasoning from awareness of the measure to effectiveness of the policy, mostly for lack of data, it surely provides evidence of the information asymmetry in Italian society, one that considerably disadvantages the worst-off.

¹⁵ De Angelis et al. (2019), for instance, have looked at the distribution of poverty across the Italian territory and the number of beneficiaries of the policy. In the absence of micro-data, their analysis is mostly descriptive but does point in the same direction as our findings.
6 Conclusion

As of today, all EU member states have income support policies in place. Facing enduring poverty rates and social exclusion, phenomena worsened by cyclic economic downturns, all EU member states have implemented measures aimed at alleviating the hardship of the worst-off. Yet, most these policies present modest track records. Part of the reasons why lies with relatively low take-up rates across member states. The question why people would not apply for benefits they are entitled to, has been posed and answered elsewhere. Differently, very few studies have investigated whether the most vulnerable, i.e., the targeted population in most instances, know about the existence of such policies. The results of our study show that they do not. We show that individuals living in dire conditions do not know about income support policies; particularly so for the little educated, inactive, women, and people living in the south of the country, where the economic prospects are scarcer.

Such findings shed light on a phenomenon that needs to be tackled if policymakers want to, first, implement effective policies and, eventually, reduce poverty. Reaching out to potential beneficiaries is of the utmost importance, as is the way to do it. Targeted outreach campaigns, although fundamental, may not be enough if the channels through which the information is passed are not the channels through which the vulnerable gather information. Our paper provides evidence on the knowledge gap that characterizes income support policy in Italy. We show how vulnerable groups are also those not knowing about the policies designed for them.

The evidence of the information asymmetry that our paper stressed out is crucial in the current framework of the redesigning of the public policies aimed at the poverty eradication in Italy. The conclusion we can draw therefrom is that targeted outreach campaign is of absolute necessity to increase knowledge of the measure and, thereby, increase take-up rates. That being stated, further research needs to be conducted to understand how to go about informing vulnerable groups. Following previous studies (Herd et al. 2013; Daigneault and Macé 2019), outreach campaigns, enrolment via community-based organizations, as well as actively inform potential participants of the existence of the program can be considered fundamental actions in order to reach the potential recipients.

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Declarations

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