Understanding and Identifying Poverty and Vulnerability in Italy

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KEYWORDS

Poverty Risk

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ABSTRACT

This thesis examines the factors contributing to poverty and vulnerability in Italy, focusing on how households become poor and the risks they face due to adverse circumstances. Vulnerability to poverty, an ex-ante measure, captures the probability of a household falling into poverty in the future, making it crucial to identifying those most at risk. Based on the Survey of Household Income and Wealth (SHIW), the concept of vulnerability to poverty will be presented both qualitatively, by reviewing the most significant definitions in the literature, and quantitatively, through logit and regression models, implemented to identify the poverty risk thresholds with a dynamic approach, associating the predicted probabilities to be vulnerable to the equivalent household income. The results indicate significant regional disparities, with households in southern Italy, those lacking higher education and those unable to save, facing higher risks of poverty. Vulnerability analysis also reveals that vulnerable households are not completely conscious about their condition, making the study even more important in terms of information. In Italy the number of vulnerable households is almost double the number of the effectively poor households, reinforcing the idea that it is important to prevent poverty trap or situation in which households are unaware of their risky status. Policy implications highlight the need for targeted interventions, including enhancing social safety nets, promoting financial literacy and addressing regional inequalities.

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PALAVRAS-CHAVE

Risco de Pobreza

Vulnerabilidade

Disparidades entre Agregados Familiares

Determinantes Socioeconómicos

Política Social

RESUMO

Esta tese examina os fatores que contribuem para a pobreza e a vulnerabilidade na Itália, focando-se em como os agregados familiares se tornam pobres e nos riscos que enfrentam devido a circunstâncias adversas. A vulnerabilidade à pobreza, uma medida ex-ante, capta a probabilidade de um agregado familiar cair na pobreza no futuro, tornando-se crucial para identificar as pessoas em maior risco. Com base no Inquérito ao Rendimento e Riqueza dos Agregados Familiares (SHIW), o conceito de vulnerabilidade à pobreza será apresentado qualitativamente, através da revisão das definições mais significativas na literatura, e quantitativamente, através de modelos logit e de regressão, usados para identificar os limiares de risco de pobreza com uma abordagem dinâmica, associando as probabilidades previstas de ser vulnerável ao rendimento equivalente do agregado familiar. Os resultados indicam disparidades regionais significativas, com os agregados do Sul de Itália, aqueles sem educação superior e os que não conseguem poupar enfrentando maiores riscos de pobreza. A análise também revela que os agregados vulneráveis não estão completamente conscientes da sua condição, o que torna o estudo ainda mais importante em termos informativos. Na Itália, o número de agregados vulneráveis é quase o dobro do número de agregados efetivamente pobres, reforçando a importância de evitar a armadilha da pobreza, onde as famílias desconhecem seu estatuto de risco. As implicações políticas destacam a necessidade de intervenções específicas, como o fortalecimento das redes de segurança social, promoção da literacia financeira e a redução das desigualdades regionais.

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Contents

1. INTRODUCTION

Since its establishment in 1944, the World Bank has made poverty reduction a central part of its mission, offering extensive research, data and policy recommendations to address poverty globally. One of its most notable contributions, the $1-a-day poverty line, emerged from a scientific study in the 1980s and was adopted by the Bank in 1990 as a benchmark for measuring poverty. This measure gained widespread recognition when it became part of the Millennium Development Goals, serving as a global standard for poverty tracking. However, this poverty line has faced criticism for its theoretical and practical limitations, often leading to underestimations of poverty in certain countries. In the early 2000s, the World Bank expanded its focus beyond simply measuring poverty as a static, ex-post condition, to address vulnerability, i.e. the risk of falling into poverty due to external shocks such as economic downturns, climate change or pandemics. The World Development Report (WDR) 2001 marked a significant shift by recognizing that poverty is not a fixed state but a dynamic process, with households moving in and out of poverty over time. Understanding vulnerability to poverty became crucial in predicting who is most at risk and guiding more proactive, preventive measures.

In recent years of the Covid-19 pandemic, the persistent socio-economic crisis in Europe have renewed interest in understanding the household's financial situation, evaluating poverty risk with a dynamic approach. This type of study had a big expansion next to the financial and the subsequent sovereign debt crisis of 2007 where economists and financial institutions started to closely monitor all microeconomic information in order to identify possible distress among households and, eventually, some possible financial problems. The economic downturns and the increase of the social inequalities highlighted the need to focus academic and policy attention on the conditions that lead households into poverty, or to become poor in the near future. Poverty has long been a central issue in economics, where researchers try to understand its causes, consequences and potential solution.

The concept of vulnerability to poverty has only recently gained prominence, helping to identify those at risk before they actually fall into poverty, allowing for more preventive measures. In fact, in statistical terms, if the poverty represents the realization of the causal variable related to the well-being, the vulnerability to poverty represents the probability function of that variable. The vulnerability of a family depends not only on the presence of negative shocks, but also on the capacity, or incapacity, to respond to risk: the strategy available to the household

may be a preventive one (the household may insure itself against risk) or a reparatory one for the damage caused by the shock through a decumulation of savings, for example.

Vulnerability recalls a forward-looking viewpoint rather than a posterior assessment and some general aspects, described by Dercon (2001) are represented by these points: it relates to a future loss in some benchmark of welfare; it depends on uncertain events; it depends on the nature of risk and the ability to react to the risk itself; it depends on the time horizon of the risk and the reaction to this latter. The above-listed aspects allow considering both ex-post policies on individuals and households already in a poverty state and ex-ante policies for removing those factors that can lead to poverty (Chaudhuri et al. 2002). In general, the world development report of 2001 (World bank 2001) suggests that an economic agent (an individual or a household) should be considered vulnerable to poverty if he faces a relevant current risk of becoming poor (or remaining poor) in the future. In fact, vulnerability implies studying poverty from a dynamic perspective: as Hoddinot and Quisumbing (2003) stated, the poverty is an ex-post measure of well-being, while vulnerability to poverty is an ex-ante measure. So vulnerability can be defined as the propensity, measured ex-ante, to become poor in the future, and its identification makes it possible to identify that segment of the population most at risk in the case of adverse events. It represents a state of potential or latent poverty, which may affect not only those who are currently poor but also individuals who have a high probability of falling into poverty in the near future. It is important to remember the idea of Moser (1998) that poor people are usually among the most vulnerable, but vulnerable people are not necessarily poor.

While there is a growing body of research on poverty, specifically in Italy, much of it did not fully explored all the aspects of the vulnerability, in particular regard to the relationship with regional disparities, labour market dynamics and all the most important socio-economic characteristics of the household itself. This thesis aims to fill this gap by focusing on vulnerability within Italy, analysing the financial conditions of Italian households across time. Building on the extensive work done by the World Bank, the paper recognizes the importance of continuing to study poverty from a dynamic perspective. The World Bank's contributions have laid a strong foundation for understanding the shifting nature of poverty, but the increasing frequency of global crises, such as the Global Financial Crisis and COVID-19, has made it more critical than ever to further explore the factors that drive households into vulnerability.

By focusing on how poverty evolves and how households become vulnerable, this analysis seeks to contribute to the growing body of research that emphasizes the need for preventive

approaches rather than reactive solutions. Understanding poverty as a dynamic phenomenon, rather than a static state, is essential for designing more effective policies. This perspective allows for the identification of vulnerable groups before they fall into poverty, enabling interventions that can mitigate risks and prevent long-term economic hardship. Therefore, in line with the World Bank's evolving approach, this thesis quantifies poverty and vulnerability in the Italian context, and the ways in which different socio-economic and regional factors contribute to household financial instability. The analysis is performed on longitudinal data from Bank of Italy's Survey on Household Income and Wealth (SHIW) for 2014 and 2016, where same households were examined across time, allowing to analyse more precisely the change of the variables between the two periods.

Key questions guiding this research include: What are the socio-economic characteristics of households poor and most vulnerable to poverty in Italy? How can vulnerability to poverty be effectively measured in the Italian context? Hence the purpose is to answer those questions by developing two different conceptual and empirical frameworks: the first one will assess the likelihood of different households falling into poverty; the second one, once the profile of poor has been delineated, establish the expected equivalised income of households and it will be related to household's estimated probability of becoming poor, identifying the line of vulnerability. Hence, this work has a dual purpose. Firstly, it seeks to enhance the descriptive analysis of absolute poverty dynamics in Italy by incorporating the concept of "vulnerability to poverty,". Secondly, it aims to demonstrate how measuring vulnerability can significantly impact both the analysis of wellbeing and the formulation of policy. Therefore, this study will present a detailed case study of Italy, examining the socio-economic factors that contribute the most to vulnerability, by employing predictive statistical model and inferential statistical methods. The choice of the time period between 2014 and 2016 is due to the fact that it is important to consider a stable macroeconomic situation because households do not have to be under some negative shock that cause some changes in the behaviours or in the choices of the households. In this way the bias due to external variable will be limited, considering a period that seems to be macroeconomically stable in economic and social terms.

The research is expected to reveal significant regional variations in poverty and vulnerability to it, with South region displaying higher levels of risk due to weaker social safety nets, worst economic conditions and greater exposure to economic shocks (the so called "questione meridionale", defined as the gap between north and south of Italy). Moreover, some significant difference will be found also for different level of educations and different occupations.

Vulnerability analysis turns out to be a useful tool which should complement the traditional analysis of poverty.

This paper is structured as follows. Section 2 provides a detailed review of the literature on poverty and on vulnerability to poverty. Section 3 presents the case study, discussing the model definition and the data used for the empirical analysis. Section 4 discusses the findings and their implications. Finally, Section 5 concludes with recommendations for future research and some potential policy interventions.

2. LITERATURE REVIEW

The relevance in analysing vulnerability is related to the growing interest in including the concept into the design and implementation of social development strategies. Under the normative assumption that vulnerability causes insecurity and a reduction of welfare, it should be a central component of public actions to ensure a minimum level of protection. Vulnerability to poverty is an ex-ante measure of the likelihood of becoming poor in the future. The World Bank defines vulnerable to poverty (which will be defined for the rest of the text only as vulnerable) as the individual who has a significant probability of becoming poor in the next year. The future well-being of an individual or household is strongly related to current income and consumption, but there is within it a component of risk of adverse shocks in the future. Indeed, the World Bank states that vulnerability measures resilience against shocks, that is, the likelihood that a shock will result in a reduction in well-being. There are several ways for measuring the vulnerability to poverty, based on different concepts used in defining the vulnerability itself. Fujii (2016) identified three primary methods (not mutually exclusive):

- a welfarist approach, that refers to the microeconomics principles postulating that economic actors are rational and they act to maximise their benefit. Since economic welfare is not directly observable, the welfarist school proposed to consider real income and consumption expenditures as indicators of welfare;
- an expected poverty approach, that relates vulnerability measure to how likely it is for a subject to fall into poverty in a given length of time. Vulnerability to poverty regarded as a probability has been extensively used because of its straightforward interpretation, even if the operative translation requires a huge amount of data.
- an axiomatic approach (introduced by Calvo and Dercon 2005) that considers vulnerability as the magnitude of poverty's threat and the consequent feeling of insecurity. In this sense, vulnerability is not merely viewed as low expected welfare but

is related to dangers or threats. Vulnerability measure is derived from a set of axioms, which lists the properties that an ideal vulnerability measure should satisfy.

Alwang, Siegel and Jorgensen (2001) define five principles for the concept of Vulnerability:

- vulnerability is a forward-looking concept that determines the likelihood of experiencing a negative change in well-being in the future;
- an individual or household is defined as vulnerable according to this loss of well-being, which depends on the realisation of uncertain events;
- the level of vulnerability of individuals depends both on the characteristics of the risk of adverse events and on the ability of households to respond effectively if they happen;
- vulnerability is highly time-dependent, since an individual is vulnerable, currently, to the risk of an adverse event happening in the future. The risk response itself is time-dependent, since its effects and effectiveness may last for more than one period;
- poor individuals and individuals at risk of becoming poor are more likely to be vulnerable because of their limited access to assets and limited ability to respond effectively to adverse events.

Strictly correlated to this last principle, there are some authors that try to expand their study on poverty to a bigger macro-level: for example, Aart Kraay and David McKenzie (2014) demonstrate the presence of a "poverty trap", that is a set of self-reinforcing mechanisms whereby countries did not manage to come out from poverty. Intuitively, the concept of poverty trap at country-level is strongly linked to a micreconomic foundations, meaning that this trap exists together with an household-level poor situation. Therefore, the general idea is that the current poverty might be what is causing future poverty. In this context, Fitz and Suresh (2020) highlight how poverty traps function across different levels of society, showing that systemic issues limit the ability of households to escape poverty. This structural vulnerability has been exacerbated by crises like COVID-19, as demonstrated in Brazil by Hohberg et al. (2020), where multidimensional deprivation analysis reveals how the pandemic deepened existing inequalities. Meanwhile, research by Kraay and McKenzie (2014) revisits poverty traps, debating their empirical existence and emphasizing that they remain significant in disadvantaged regions, suggesting that certain households are perpetually trapped without external intervention. In general, the empirical literature on poverty traps is most of time represented by estimating a dynamical nonlinear model (the so called "S-shaped relationship") between income or assets today to those in the previous period, but it has very mixed results.

In fact, Jalan and Ravallion (2004) try to implement this study in China, unfortunately finding no evidence, and same for Lokshin and Ravallion (2004) in Russia and Hungary. While, trying in more undeveloped countries, as Kenya Madagascar and south Africa, Barrett et al. (2006) and Adato Carter and May (2006) find a sort of poverty trap, analysing the asset dynamics over time. Similarly, in more recent years, Clare A. Balboni et al. (2021) provided an empirical test for the presence of poverty traps using individual-level panel data in Bangladesh. Their findings suggest the presence of a poverty threshold, where households starting with productive assets below this threshold remain trapped in poverty. In contrast, households that surpass this threshold can accumulate capital and gradually reach the asset levels of wealthier groups. This upward mobility enables them to transition from casual labor to more productive activities which further accelerates their asset accumulation.

Another approach is represented by Machine learning, such as those in Huang Zixi's (2021) and Sohnesen and Stender's (2021) work, that provide more precise predictive models for poverty, enhancing the ability to target interventions for vulnerable households. These advanced methodologies, like random forest models, offer better prediction accuracy than traditional methods, improving the design of anti-poverty programs. Studies on financial inclusion (Koomson et al., 2020) also indicate that enhancing access to financial services can reduce vulnerability by providing households with tools to weather economic shocks. The interplay of shocks, structural poverty and innovative methodologies to predict and address poverty highlights the need for comprehensive, context-sensitive policies. Long-term studies like Blattman et al. (2020) show that well-designed interventions, such as grants, can have sustained impacts on poverty reduction. Together, these studies point to a multifaceted understanding of poverty, one that considers immediate vulnerabilities and long-standing poverty traps while incorporating modern predictive tools to better understand and tackle the problem.

Focusing on the Italian context, many other authors tried to conduct also some more in-depth analysis, to try to better represent the Italian situation and to highlight all the real problems related to poverty. For example, Brandolini and D'Alessio (2001) analysed the income distribution in Italy, highlighting the persistent regional disparities that exacerbate poverty levels, particularly in the southern regions. In particular, their research underscores the structural challenges that contribute to long-term vulnerability among disadvantaged populations. Similarly, Saraceno (2015) explores the multifaceted nature of poverty in Italy, emphasizing the role of social exclusion in perpetuating economic hardship. In particular the study suggests that poverty in Italy is not merely a matter of low income but is closely linked

to limited access to essential services, such as healthcare and education, which reinforces vulnerability. Beyond the Italian context, global research also offers valuable insights into the dynamics of poverty and vulnerability. In a more recent study, World Bank (2018) provides a comparative analysis of poverty trends across Europe, identifying key risk factors such as unemployment, low educational attainment, and precarious employment, drawing attention to the increasing prevalence of "working poor" in Italy, where despite being employed, individuals and families remain at risk of falling into poverty due to insufficient wages and unstable job conditions. Collectively, these studies illustrate the complex and interrelated factors contributing to poverty and vulnerability at micro and macro level. The subsequent analysis of the data will build on these insights, examining the specific conditions under which poverty persists in Italy and identifying potential avenues for mitigating vulnerability among at-risk populations.

3. DATA AND METHODOLOGY

To lead this analysis, it is used the Survey on Household Income and Wealth (SHIW), a survey conducted by bank of Italy to know economical and financial behaviours of households. The peculiarity of the SHIW is the longitudinal data collection: in the sample there are households interviewed for at least two consecutive surveys allowing longitudinal analysis. This feature makes it possible to understand the development of the economic variables within the panel households over time, as well as to increase the degree of precision of the analysis on the changes detected between one period and the next. In particular for this analysis two surveys from 2014 and 2016 has been taken.

3.1 TIME PERIOD BIAS

The choice of the years is due to the absence of negative significant shock that can influence the decisions and the behaviours of the households. In analyzing the economic conditions between this period, it was crucial to consider the potential for a time period bias, a distortion in the analysis caused by significant economic shocks or fluctuations during the period studied. To demonstrate the economic stability of Italy between 2014 and 2016 four critical macroeconomic indicators will be analysed: Gross Domestic Product (GDP), public expenditure, unemployment rate and household food expenditure. Each of these indicators

serves as a pillar to assess the overall economic environment and its impact on Italian households during the period in question. All the data were taken from the Italian National Statistics Institute (ISTAT microdata), a public research organization that serve the community through the production and communication of high-quality statistical information, analyses and forecasts in the economic, social and environmental fields.

FIGURE 1: TREND OVER TIME OF GDP (1A) PUBLIC EXPENDITURE (1B) UNEMPLOYMENT (1C) AND FOOD EXPENDITURE (1D)

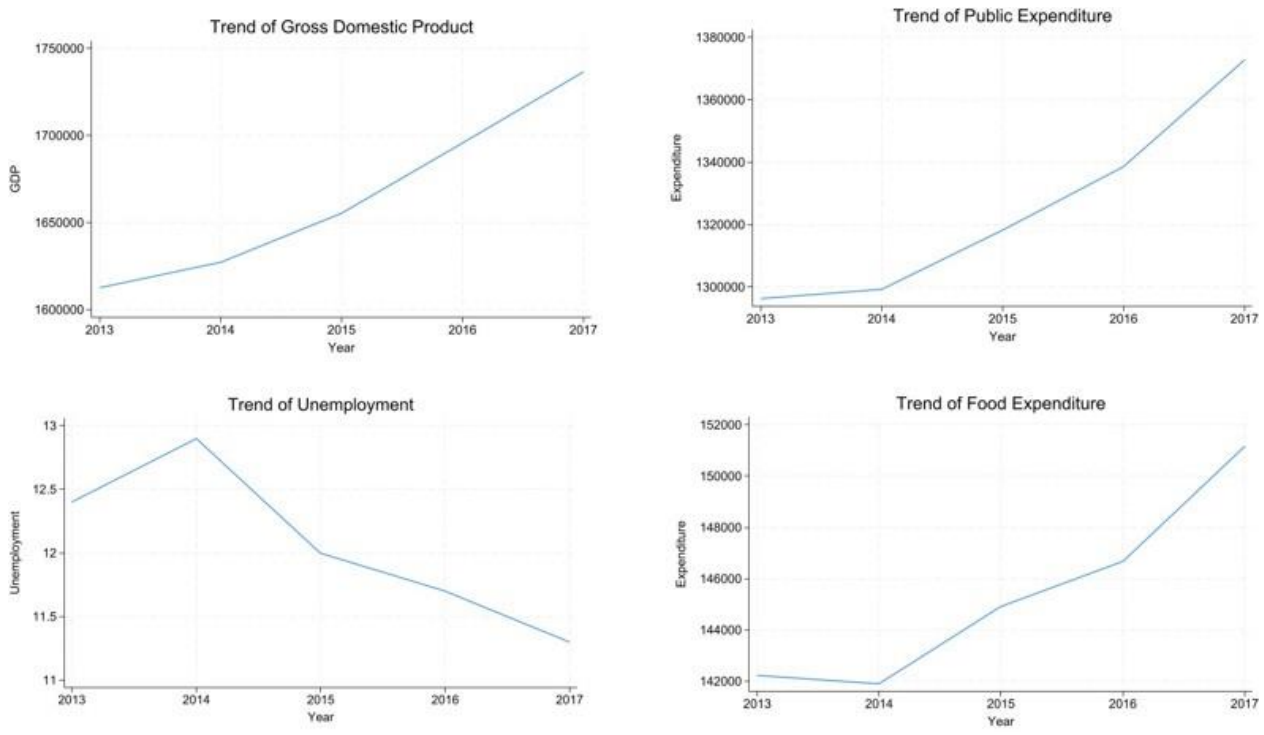


Figure 1 reports all the key macroeconomic variables during the years 2013-2017 in order to analyse their trends. The gradual increase in GDP (Figure 1A) reflects a period of economic resilience, indicating that Italy was experiencing moderate economic growth without significant disruptions. This steady GDP growth suggests that the economy was not undergoing severe economic downturns, which could have negatively impacted household income and consumption. The second graph (Figure 1B) shows the trend in public expenditure over the same period. Public expenditure is a crucial factor in stabilizing an economy, particularly in times of uncertainty. The stability in government spending during these years indicates consistent fiscal policies aimed at maintaining economic stability. Such stability is essential for sustaining public services and social safety nets, which support households, especially during potential economic downturns. The third graph (Figure 1C) focuses on the unemployment rate,

a direct indicator of economic health. A stable or declining unemployment rate during the period under review suggests that the labour market was not experiencing significant shocks. Low unemployment rates generally correlate with higher household confidence and spending, as more individuals have access to steady income, reducing the risk of economic hardship for families. In this case it slowly grow in the first year considered, but after this, the continuous decline in the percentage of unemployment is a sign of stability and better financial condition for the country. Finally, the fourth graph (Figure 1D) presents data on household food expenditure. Food expenditure is often considered a reliable indicator of economic well-being at the household level, as it is a basic necessity. The stability or increase in food expenditure during this period is indicative of households' ability to maintain their standard of living, suggesting that they were not experiencing significant economic stress or reductions in income. The analysis of these four indicators collectively supports the conclusion that Italy was in a period of relative economic stability between 2013 and 2017. The steady GDP growth, consistent public expenditure, declining unemployment rate and sustained household food expenditure all suggest that Italian households were not under severe economic tensions during these years.

Consequently, this period serves as a valid baseline for further examining the behaviour and financial health of Italian families, free from the distorting effects of significant negative economic shocks (absence of temporal bias). In fact, the data indicates an absence of such a bias, evidenced by the stability observed across key macroeconomic indicators. This lack of time period bias allows for a more accurate and reliable assessment of Italian households' economic behavior, as their decisions were not influenced by any extraordinary economic disruptions during this time. In this context, the analysis will be conducted on around 4000 households, that answered to both the surveys:

TABLE 1: SAMPLE SIZE

Year	Panel Households	New Households	Total Sample
2014	4459	3697	8156
2016	3804	3616	7420

3.2 INCOME ADJUSTMENTS

In line with the Bank of Italy's approach, in order to measure poverty in 2014, net disposable income was chosen as the index of well-being. It reflects the particular characteristics of the household, both in terms of sources and uses, and is defined in aggregate terms, i.e. taking into account the sum of income from: employment, pensions and transfers, self-employment, business work and capital income:

TABLE 2: INCOME COMPONENTS

Total net earned income (net of tax and social security contributions)
1. your average monthly net earnings (including overtime) times the number of months worked
2. additional monthly salary ("13th month" salary, "14th month" salary, etc.)
3. bonuses or special allowances
4. other items (family allowances, productivity bonuses, sales commissions, etc.)

In empirical analysis of household income, using equivalent income is crucial for several reasons, especially when analyzing the economic well-being of households;

- First, it addresses economies of scale, in fact larger households can share resources (like housing, utilities, and groceries) and thus may not need as much additional income per person as smaller households to maintain the same standard of living;
- Second, it considers a fair comparison across households because larger household might have a higher total income than a smaller one, but this does not necessarily mean its members are better off individually. So, equivalent income standardizes income by adjusting for the number and age of household members, allowing for a fairer comparison across households with different structures.

In particular, the scale used is the modified OECD equivalence scale, which assigns different weights depending on the number and age of the members: 1 to the first adult, 0.5 to all other adult members and 0.3 to other members under 14:

$$S.Eq. = 1 + 0.5(N_{adults} - 1) + 0.3 * N_{kids.14}$$

On the basis of equivalence scales, one can thus define equivalent income, i.e. the welfare indicator by which poverty status is determined: Equivalent Income = Net Disposable Income / Equivalence Scale . The next step is to determine the poverty line.

3.3 STATISTICAL METHODOLOGY

In this analysis, the approach proposed by the Bank of Italy was adopted, which defines the poverty line as 50% of the median equivalised income. It was found that in 2014 the poverty line had a value around 9500€. Once the poverty line is identified, one can easily identify the individuals in poverty, i.e. those whose equivalent income is less than or equal to the identified line. This will reveal the headcount ratio (the number of poors households over the total population) given by H.R. = n_{poors}/N_{total}, which in 2014 is 9.33%. The methodology chosen to analyse the profile of vulnerability to poverty in Italy in 2014 takes its cue from the research work of L. Lopez-Calva and E. Ortiz-Juarez (2014) and that of A. de la Fuente, E. Ortiz-Juarez and C. Rodriguez Castelan (2015). In their articles, the vulnerability to poverty is identified using a modified poverty line, which contains within it not only the level of income or consumption needed to survive, but also the part relating to the ability of households to cope with adverse events. After identifying vulnerable individuals, the authors claim that it is possible to associate the equivalent income level with the probability of falling into poverty in the future. For this analysis, the panel samples of the Bank of Italy SHIW survey will be used, i.e. households that responded to the questionnaire in both 2014 and 2016; in particular, vulnerability to poverty in 2014 will be studied. The methodology used is divided into two phases:

1. In the first phase, a logistic regression is performed where the dependent variable is the poverty status in 2016 and the independent variables represent the socio-economic characteristics of households in 2014;
2. In the second phase, a linear regression is conducted to analyze the relationship between the logarithm of the equivalent income and the same socio-economic variables identified in the first step, in order to associate each income level with the probability of becoming poor in the future.

To take a screenshot of the situation, the poverty transition matrix is constructed for the two years under consideration, considering households that changed or not their condition from poverty to non poverty and viceversa. In this way there will be:

- the never-poor households, i.e. those that have always remained above the poverty line in the two years;

- the always poor, i.e. households that are classified as poor in both 2014 and 2016;

- the ex-poor, i.e. those households that came out of poverty from 2014 to 2016;

- the new-poor, i.e. those households that were not poor in 2014 but became poor in 2016.

TABLE 3: POVERTY MATRIX

YEAR 2014	**YEAR 2016**	
	NON POOR	**POOR**
NON POOR	87.71%	4.73%
POOR	2.96%	4.60%

The first step is to define a logistic regression model in which the dependent variable is the probability of becoming poor in the period following the initial period (general logit model $p_{i,t}$ = Pr[y = 1|X]). By including some representative characteristics, the objective is to predict the probability of falling into poverty for the households in the sample and then to subsequently estimate their vulnerability. In formal terms, the probability of falling into poverty will be defined as:

$P_{i,t} = Pr(poor_{i,t+1}|X_{i,t}) = F(X_{i,t} * \beta_{i,t})$

where $p_{i,t}$ represents the probability at time t , with t = 2014, of becoming poor in period t + 1, i.e. in 2016, and the logistic cumulative density function is given by:

$$\Lambda(X'\beta) = \frac{e^{XF\beta}}{1+e^{XF\beta}}$$

The variable $poor_{i,t+1}$ represents the poverty status in the period t +1 that is the 2016, and takes the value 1 if households are classified as always poor or newly poor and value 0 in other cases:

$$Poor_{i,t+1} = \begin{cases} 1 \text{ if always poor or new poor} \\ 0 \text{ if never poor or ex poor} \end{cases}$$

The independent variables identified by the vector X refer to all socio-economic characteristics of the households and the head of household. The head of household chosen in this work is the individual within the household who responded to the survey (whose value of the variable "NORD" corresponds to '1'). The informations included for the analysis are represented by:

socioeconomic characteristics of household, like geographical location, type of dwelling, , employment information and educational level.

- Geographical area: the variable divides the Italian territory into three macro-areas: North, Centre and South;

- Home ownership title: divides the type of home ownership into two categories: the first is owned, usufruct and free housing; the second category is rented housing;

- Educational qualification: variable indicating the educational qualification of the highest income earner within the household. Three modes are taken into account: lower secondary school or lower qualification, upper secondary school diploma and university degree or higher;

- Occupational Status: variable indicating the type of occupation of the household head or, in the case of a non-worker, the non-occupational status category. They are divided into: employed; self-employed and well-off; unemployed; housewife and other non-occupational status; retired;

- Deposit: variable indicating whether the household owns at least one bank or postal deposit;

- Savings: variable indicating whether the household has managed to save or not in the current year and it is divided into three modes: gain, break-even or loss;

The variables taken into account are only dummy or categorical and are depicted in table 4:

TABLE 4: DESCRIPTION OF THE VARIABLES

Variable Name	**Description**	**Value**
Abitation	Type of Housing Enjoyment	1 = Ownership, usufruct, redemption, free use 0 = rent
Educational Qualification	Educational Qualification Held by the Head of Household	1 = None, primary school certificate, lower secondary school certificate 2 = Vocational secondary school diploma, upper secondary school diploma 3 = 3 or 5 year university degree/higher education

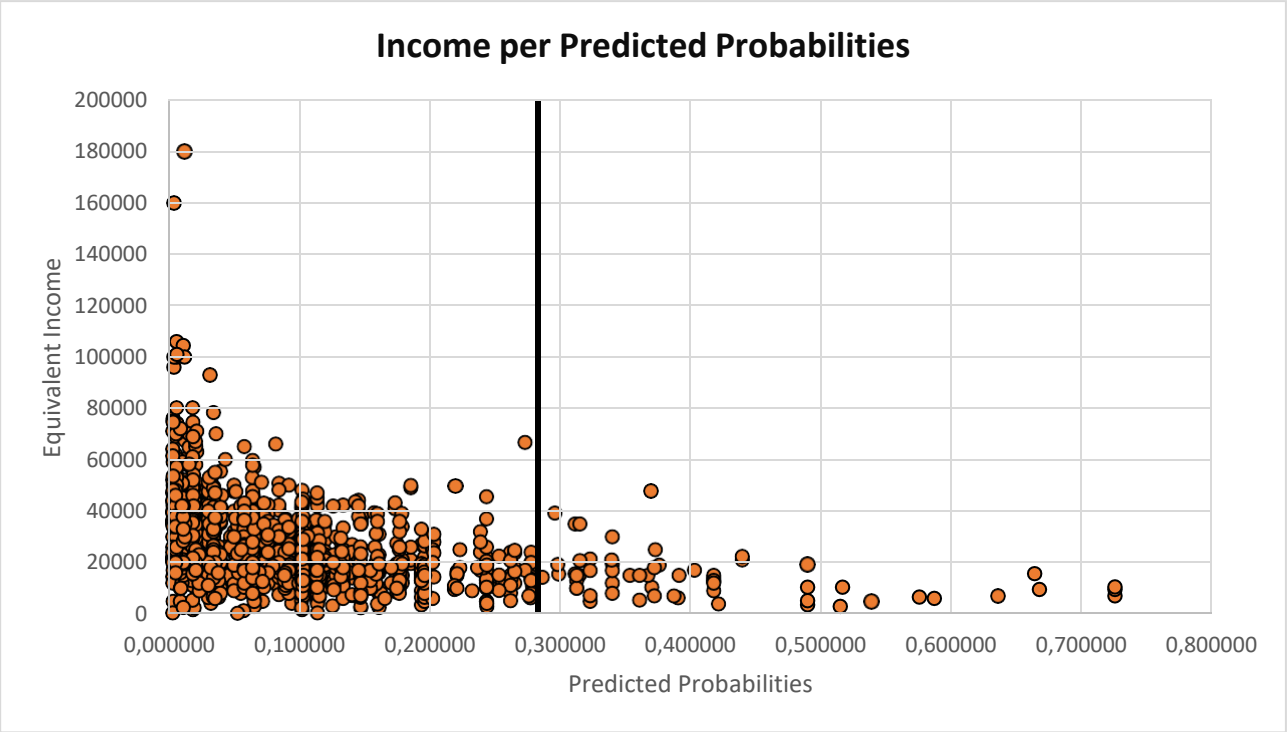
		diploma, postgraduate qualification
Area	Geographical Area	1 = North 2 = Centre 3 = South and Islands
Occupation	Employment Status	1 = Blue-collar worker 2 = Office worker or school teacher 3 = Cadre or manager 4 = Sole proprietor/member of the arts or professions 5 = Other self-employed 6 = Pensioner 7 = Other not-employed
Deposit	Ownership of at least one bank or postal deposit	1 = At least one bank or postal deposit 2 = No bank or postal deposit
Savings	Saving situation in the currently year	1 = Spent less than its entire yearly income and succeeded in saving 2 = Spent its entire yearly income and did not manage to save anything 3 = Spent more than its entire yearly income, drawing on savings or borrowing

3.4 LOGIT MODEL

The logistic regression allows us to identify vulnerability to poverty in Italy, i.e. the estimated probability of becoming poor in the period t+1. At the same time, all individuals, even the wealthiest ones, have an associated predicted probability that, however small, is different from zero. It is therefore necessary to define a threshold value within which an individual can be defined as vulnerable. So, after calculating the predicted probabilities of falling into poverty using the logistic regression model, the next step is to identify a suitable threshold for

classifying households as vulnerable to poverty. This threshold will help in determining which households, while currently above the poverty line, are at significant risk of falling into poverty.

FIGURE 2: DISTRIBUTION OF THE EQUIVALENT INCOME DEPENDING ON THE PREDICTED PROBABILITIES OF THE LOGIT MODEL



To identify them that are particularly at risk, the distribution of the predicted probabilities was considered and selected the 95th percentile as the threshold. This choice is justified for several reasons: by selecting the 95th percentile, the focus will be on the top 5% of households with the highest predicted probabilities of falling into poverty. This method is highly selective and ensures that only those households with a considerable risk are classified as vulnerable. The rationale behind this choice is that targeting the most at-risk households allows for more effective allocation of resources and policy interventions, ensuring that those who are most likely to fall into poverty receive the necessary support. The 95th percentile threshold is expected to result in a manageable number of households being classified as vulnerable. Given the total population size, the top 5% represents a small but significant group that can be feasibly targeted with available resources. This approach ensures that the identified group is not too large, which would dilute the effectiveness of interventions, but rather is focused enough to allow for impactful policy measures. After identifying the 95th percentile as the threshold for vulnerability, the corresponding income level is calculated that aligns with this percentile of predicted probabilities: the level corresponding to the predicted probabilities at 95^{th} percentile

is 0,2725672 (represented in graph 2 with the black line) and the corresponding income value is 12640,92€. This income level provides a benchmark for understanding which households, based on their income, are at significant risk of poverty, or vulnerable to poverty.

Going into detail, the percentage of vulnerable households in the year 2014 is 16.67%, more than 75% of the percentage of poor households. To better understand the vulnerable household's situation, table 5 represents in percentage terms the vulnerability matrix of households that change or not their economic condition during the two years:

TABLE 5: VULNERABILITY MATRIX

YEAR 2014	YEAR 2016	
	NON VULNERABLE	VULNERABLE
NON VULNERABLE	77.98%	7.63%
VULNERABLE	5.13 %	9.27%

3.5 GEOGRAPHICAL AND SELF-REPORTED POVERTY DISTRIBUTION

In 2016 the vulnerable households increased by around 15% respect to 2014, in particular most of vulnerable households in the first period remain in the same situation two year after. At geographical level, most of vulnerable households come from South Italy (as predicted in the first model) with a percentage of around 65% respect to the North Italy. In particular the worst regions in terms of vulnerability are "Campania" with around 10% of all households and "Sicily" with 12% of them. In the graph 3, there is the geographical representation of the distribution of vulnerable households in Italy. The vulnerable population is graphically spread like that:

FIGURE 3: DISTRIBUTION OF VULNERABLE HOUSEHOLDS IN ITALY

- Green regions: Less than 2.5%
- Yellow regions: Between 2.5% and 5%
- Orange regions: Between 5% and 7.5%
- Red regions: More than 10%

Another way to try to represent the situation in Italy is by trying to analyse what households think about their situation. Therefore, the data in Table 6 provides insights of self-reported conditions felt by households classified as "Poors" and "Vulnerables" in 2014. The table reveal a distinction in how these groups perceive their financial conditions that can be indicative of their awareness of their economic realities. A large proportion of poor households (44.37%) consider their situation as "Very Difficult," which suggests a high level of awareness of their economic struggles, while another 23.24% find it "Difficult" and 18.31% experience "Some Difficulties". In contrast, only 2.82% of poor households describe their condition as "Easy" and no households reporting it as "Very Easy." So, the very low percentage of poor households that perceive their situation as "Easy" or "Very Easy" indicates that these households are highly aware of their difficult financial situation, with most recognizing the severity of their circumstances. On the other side, while still experiencing hardship, vulnerable households report slightly less severe self-reported conditions compared to the poor. For example, 37.01% of vulnerable households describe their situation as "Very Difficult" and 23.62% as "Difficult" A notable proportion (16.54%) find their condition "Quite Easily," and a small minority (0.79%) even describe it as "Very Easy." The presence of households within the vulnerable category that

report their condition as "Quite Easily," "Easy," or "Very Easy" suggests a less acute awareness or acknowledgment of their financial challenges compared to those who are classified as poor. The data indicates that poor households are more acutely aware of their financial difficulties compared to vulnerable households. This heightened awareness among the poor may stem from the more immediate and severe economic challenges they face. On the other hand, vulnerable households, who may not yet experience the same level of deprivation as the poor, show a broader range of perceptions, including a slightly higher proportion who perceive their situation with less difficulty. This disparity in self-perception underscores the importance of considering both subjective and objective measures when assessing household well-being and economic vulnerability. It seems clear that households' subjective judgments of their state of well-being are more closely aligned with their actual state of poverty than with the normative state of vulnerability. Vulnerable households might not fully recognize or accept their precarious situation until it worsens, unlike poor households who are already fully aware of their dire economic status.

TABLE 6: CONDITION FELT BY HOUSEHOLDS

	Condition declared by the households in 2014					
CONDITION	Very Difficult	Difficult	Some Difficulties	Quite Easily	Easy	Very Easy
Poors	44.37%	23.24%	18.31%	11.27%	2.82%	0%
Vulnerables	37.01%	23.62%	19.69%	16.54%	2.36%	0.79%

3.6 REGRESSION MODEL

With the data collection and methodological framework established, we can now turn our attention to the outcomes of these analyses. In the following section, the results derived from the applied techniques will be presented and discussed in detail, providing insights into the vulnerabilities of the italian households. In particular, the second step is to use the same explanatory variables used in the first step to regress the trend in equivalent income in order to associate each probability of becoming poor with the corresponding expected level of income. To this end, the logarithm of household equivalent income in the year 2014 will be taken into account. In formal terms, we will have the following linear regression model:

$$\ln y_{i,t} = \alpha + \mathbf{X}_{i,t} \cdot \beta_{i,t} + \epsilon_i$$

With the data collection and methodological framework established, the attention can now turn on the outcomes of these analyses. In the following section, the results derived from the applied techniques will be presented and discussed, representing the general Italian situation into detail.

4.RESULTS

4.1 ODDS AND AVERAGE MARGINAL EFFECTS

This section presents the results of the models designed to investigate: the probability of being poor in the next period given some particular socioeconomic characteristics; the associated income to the probability of being poor and vulnerable to poverty too. In the table 7, there are the results of the logit model:

TABLE 7: LOGIT MODEL

	(1) Poverty t+1
Abitation	-0.623**
	(-2.93)
Education=1	0
	(.)
Education=2	-0.113
	(-0.54)
Education=3	-1.333*
	(-2.40)
GeographicalArea=1	0
	(.)
GeographicalArea=2	0.499*
	(2.00)
GeographicalArea=3	0.625**
	(2.77)
Occupation=1	0
	(.)
Occupation=2	-1.170**
	(-3.24)
Occupation=3	-1.140
	(-1.50)

Occupation=4	0.614
	(1.24)
Occupation=5	0.352
	(0.68)
Occupation=6	0.638*
	(2.36)
Occupation=7	0.292
	(1.17)
Deposit	-1.093***
	(-3.54)
Savings=1	0
	(.)
Savings=2	0.505
	(1.81)
Savings=3	1.521***
	(4.31)
Constant	-1.461***
	(-3.32)

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All the coefficients are significant at three different level of significancy (most of them at 99% significance level, and also 95% and 90%) except high school diploma and certain types of occupation (sole proprietor/member of the arts or professions, other self-employed and other not-employed). These results can be explained in two different ways: through the odds ratio, analysing the odds marginal effect, given by e^{β}-1, or computing on STATA the productivy average marginal effect (AME). In particular, holding the other characteristics constant at a fixed value, there will be:

- A 46.34% decrease in the odds of being poor in the next period t+1 (in 2016), if the abitation is owned and not rented by head of household. This can be explained from the fact that owning a home generally provides greater stability compared to renting. In fact renters face potential rent increases or eviction, which can lead to financial instability.
- A 73.62% decrease in the odds of being poor in t+1, if the head of households has a university/college degree. Following the human capital theory, education increases an individual's productivity and skills, making them more competitive in the labour market, reaching better-paying jobs, more stable employment and greater career

opportunities that reduce the likelihood of being poor. In fact, on average increasing the level of education by one unit, will decrease the probability of being poor by 7%, ceteris paribus.

- A 64.71% increase in the odds of being poor in t+1, if there is the geographical passage from north to centre, and a 86.84% increase, if it is from centre to south of Italy. It can be understood within the context of the "questione meridionale" and the enduring economic disparity between the north and the south of Italy. In this context, there is the south that long suffered from higher unemployment rates, lower wages and in general lack of infrastructure respect to the north characterized by higher GDP per capita, better job opportunities and more robust public services.
- Compared to blue collar workers, a 68.95% decrease in the odds of being poor in t+1, if the head of household is a office worker or school teacher, a 68.02% decrease if the head of household is a cadre or a manager and a 89,35% increase in the probability if the head of household is a pensioner. Office workers and school teachers generally earn higher and more stable incomes compared to blue-collar workers, so the lower odds of poverty reflect the relatively stable and secure nature of these occupations, which offer a steady income and protection against economic shocks through pensions, health insurance and paid leave. Cadre and managers are typically in higher-paying and more prestigious roles with greater authority and responsibility and all the financial incentives that they have respect to blue collar work can explain this significant decrease in the odds of being poor. Finally, pensioners often rely on a fixed income from pensions which may not keep pace with inflation or the cost o living and moreover there are always potential health care costs and other aging-related expenses that increases their economic vulnerability and the probability of falling into poverty respect to blue collar worker. In fact, linked to this last result, analysing the average marginal effect, on average being pensioner increase the probability of being poor in the following period by 7%.
- A 66.47% decrease in in the odds of being poor in t+1, if the head of household has at least a bank or postal deposit. Intuitively, having one of it is a key indicator of financial inclusion and the ability to save, that's important against income shocks, such as job loss, illness and unexpected expenses. So households with savings can draw on these deposits to cover needs during difficult times, preventing them from falling into poverty.

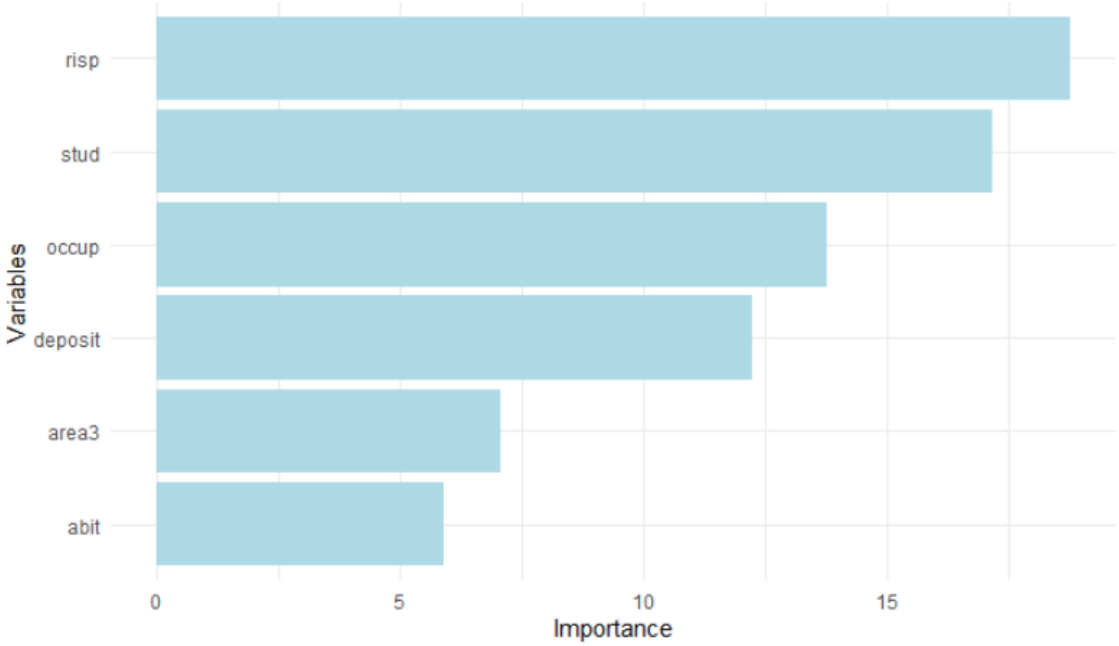
- Finally, a 65.66% increase in the odds of being poor in t+1, if the head of household spent its entire yearly income and did not manage to save anything, and a 357.45% increase in probability if he spents more than its entire yearly income, drawing on savings or borrowing. These results are the most intuitive because they are strongly linked to probability of poverty and also the most impactful thinking to the fact that if an household did not manage to save during the year, it has around 4 times more probability to fall in poverty respect to other households.

4.2 ROBUSTNESS CHECK: RANDOM FOREST ALGORITHM

The predictive ability of the logistic regression model can be defined approximately by comparing the actual value of the variable $poor_{i,t+1}$ and the value predicted by the model y_i* (considering probability threshold higher or lower than 0.5 of being poor or not poor): the model correctly predicts around 90% of cases, with a greater ability to predict non-poor households than poor households (given the fact that most of households is non-poor). However, the logit model has two several limitations that must be considered: the first is the overfitting bias, because of the presence of almost only categorical and dummy variables in the model and because of the imbalanced data that let model misclassify the minority class (poor households) because it tends to focus on the majority class. The second is that the logistic regression model assumes a linear relationship between the independent variables and the log-odds of the dependent variable but, in reality, socioeconomic factors like income, education and geographical location may interact in non-linear ways that the model cannot capture effectively. To address the limitations of the logistic regression model, the random forest model is considered as a complementary approach to capture the complexity of poverty dynamics. The idea is to use this type of machine learning algorithm to capture the non-linear relationship between variables and their complex interactions, ranking them by importance. It creates several decision trees from bootstrapped training samples and at each node of a tree, it selects a random subset of predictors to split the data. Thanks to this, the randomness reduces overfitting, improves the accuracy and the analysis becomes more robust providing more reliable predictions of household poverty in 2016 based on 2014 characteristics. In particular, the study of Sohnesen, Thomas Pave Stender, Niels. (2016), published by the World Bank, will be followed for the random forest approach that will be applied to predict the vulnerability to poverty of Italian households. The dataset is split into training and testing sets (following the

literature of 70-30 ratio) and the first one is trained with 500 trees. After training the model, the importance of each predictor is measured and ranked as reported in the table 8:

TABLE 8: VARIABLES RANKING THROUG RANDOM FOREST ALGORITHM



The Random Forest model proved to be more accurate (around 94% of correctly predictions) than the logistic regression in predicting the future poverty status. Moreover, the ranking of variable importance in the random forest almost mirrors the result of the first model. This similarity in the impact confirms the robustness and significance of the results, reinforcing the validity of the findings. The consistency across models suggests that the socio-economic characteristics, that have been used, are reliable predictors of future poverty, making the conclusions of the two models stronger.

4.3 POVERTY AND VULNERABILITY TO POVERTY LINES

Established the most predictable characteristics for vulnerable households, the second model is implemented to better illustrate the relationship between income and the predicted probabilities of falling into poverty. To do it, a linear regression analysis is performed. The regression model considers the logarithm of the equivalent income regressed for all the same socioeconomic characteristics that were considered in the first model. This regression analysis and the subsequent graphical representation allow for a clearer understanding of how income levels influence the likelihood of falling into poverty, particularly highlighting the critical income

threshold at which households become poor and highly vulnerable. In table 9, it is intuitively noticeable that most of the coefficients of the dependent variables in the linear regression are of opposite sign than the corresponding ones in the logistic regression. In fact, taking as the reference group (except for the dummy variables) the categories where a state of poverty is least associated (except for the variable of educational level), in the logistic regression success is represented by the poverty state, i.e. the state where income has a lower value than the poverty line. In linear regression, on the other hand, belonging to a different category leads to an expected decrease in income. This difference explains why the signs of the coefficients tend to be opposite between the two models.

TABLE 9: REGRESSION MODEL BETWEEN THE LOGARITHM OF EQUIVALENT INCOME AND THE OTHER SOCIOECONOMIC VARIABLES

	(1) Logwage
Abitation	0.202***
	(5.39)
Education=1	0
	(.)
Education=2	0.102**
	(2.93)
Education=3	0.252***
	(4.97)
GeographicalArea=1	0
	(.)
GeographicalArea=2	-0.0729*
	(-1.97)
GeographicalArea=3	-0.185***
	(-5.54)
Occupation=1	0
	(.)
Occupation=2	0.197***
	(4.81)
Occupation=3	0.544***
	(8.28)
Occupation=4	-0.187*
	(-2.35)

Occupation=5	-0.0460 (-0.54)
Occupation=6	-0.158** (-3.21)
Occupation=7	0.0534 (1.14)
Deposit	0.324*** (4.45)
Savings=1	0 (.)
Savings=2	-0.0836* (-2.49)
Savings=3	-0.0733 (-1.27)
Constant	9.449*** (113.92)

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Next to this model, the idea is to represent the association of the estimated probability of becoming poor with the estimated equivalent income, created by dividing the average equivalent income belonging to each probability interval. So in the figures 4 and 5, there will be:

- a representation of the strict relationship between the equivalent income and the predicted probabilities evaluated in the first step; in particular, the attention will be on the representation of the two lines recreated through the econometrical model, i.e. the poverty line (in red) and the vulnerability line (in orange);
- an analysis of the sensitivity of the vulnerability line, varying the threshold value of the probability within which a household is identified as vulnerable by setting it at different level of percentile

FIGURE 4: EQUIVALENT INCOME PER PROBABILITY OF BECOMING POOR

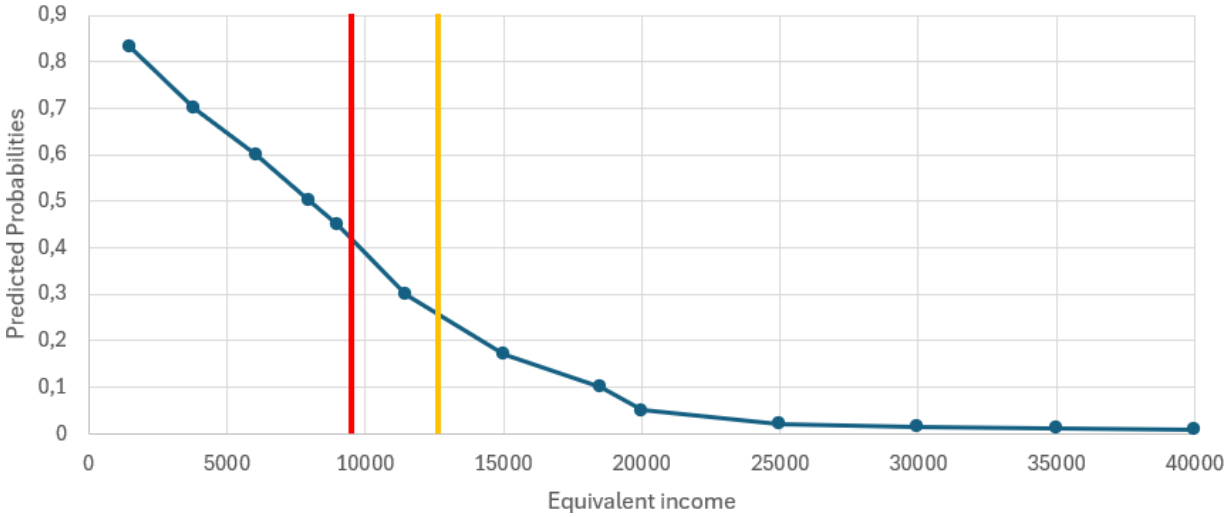
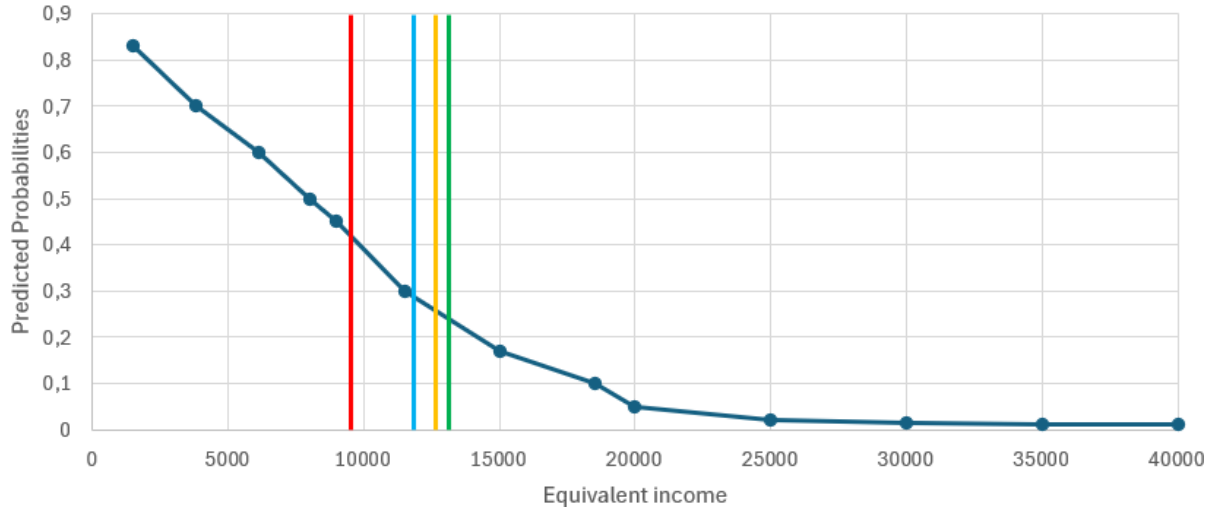


FIGURE 5: ANALYSIS OF VULNERABILITY LINE SENSITIVITY



Finally, the sensitivity of the 'vulnerability line' thus identified was analysed, varying the probability threshold value within which a household is identified as vulnerable by setting it at the new test values predicted probability = 0.3 (green line) and predicted probability = 0.25 (blue line) at correspondent income levels. As figure 5 shows, with respect to the vulnerability line, there is a greater sensitivity towards higher probability values: with the pr = 0.25 there is a positive percentage change in income of 5,07%, while with the higher probability pr = 0.3 there is a decrease in expected equivalent income of 9.4%.

4.4 LIMITATIONS

It is always important to remember that given the Survey of Household Income and Wealth (SHIW) by the Bank of Italy to study poverty and vulnerability to poverty, some potential limitations and biases may arise. For example, although SHIW aims to be nationally representative, regional disparities in response rates may exist, particularly in more remote or less populated areas and this could lead to an overestimation or underestimation of poverty in specific regions of Italy. Going deeper, survey respondents may underreport their income, especially if they receive income from informal or illegal activities and this can lead to an overestimation of poverty levels since actual income might be higher than reported. Obviously, also in the choice of the income as proxy of the poverty is in certain sense a limited choice: the focus on income and wealth may not fully capture all dimensions of poverty, such as access to public services, health, education, and social capital and this limitation can lead to an incomplete picture of vulnerability, as poverty is a multidimensional phenomenon.

Finally, the 95th percentile is an arbitrary choice and may not represent the optimal threshold for identifying vulnerability. Different percentiles could yield different results and there is no universally accepted standard for what constitutes a "vulnerable" household. Otherwise, looking at the income distribution (the logarithm of the equivalent income), the average and the median income is very similar, meaning that the distribution has not a strong negative or positive skew. So this case does not seem to be the one where the 95th percentile threshold might be influenced by outliers or extreme values in the data. In fact, it is true that if the distribution of predicted probabilities is skewed or contains outliers, the threshold may not accurately reflect the true level of vulnerability, leading to misclassification of households; but in this situation it does not seem the case.

5. CONCLUSIONS

Thanks to the Survey of Household Income and Wealth (SHIW) conducted by the Bank of Italy, this thesis has explored the complex relationship between socioeconomic characteristics and the probability of falling into poverty in Italy, evaluating the factors that contribute the most to the vulnerability. It can be possible through a logit and a regression models that have identified and quantified the key determinants of poverty and vulnerability to it. First of all, applying the method proposed by L-Calva, L. and Ortiz-Juarez, E. (2014) and by De la Fuente, A., Ortiz-Juarez, E., and Rodriguez-Castelan, C. (2015) to data, it was seen that 16.91% of Italian

households Italian households were vulnerable, a percentage that represents almost double the number of households poor (9.33%). In particular, the findings indicate that certain socioeconomic factors significantly influence the likelihood of being poor in the subsequent period. From one hand, homeownership, higher education levels, specific type of occupations (such as office workers, school teachers, cadres, and managers) and financial inclusion through savings are all associated with a reduced risk of poverty. On the other hand, regional disparities like living in southern Italy, or reliance on a pension and low level of savings during the year dramatically increase the odds of falling into poverty. These results highlight the ongoing economic disparities in Italy, in fact there is the persistent divide between the more prosperous and rich northern regions and the less developed southern regions.

Moreover, the study illustrates how income levels are intrinsically and strictly linked to the probability of poverty. The regression analysis revealed that lower income is associated with higher predicted probabilities of poverty, underscoring the critical income thresholds that delineate poverty and vulnerability. The figures 4 and 5 emphasized this relationship, providing a visual understanding of how slight changes in income can significantly change the risk of poverty. But it is important to remember that a continued growth in the quality and quantity of data is desirable, especially longitudinal data, in order to accurately identify the dynamics that lead households to be more exposed to risk. Eurostat, for example, has arranged some surveys on the condition of households in every European country and then collected in the Eu-Silc21 where, it is mandatory to have at least 5,000 panel households. However, this research is not without its limitations. The potential biases in the SHIW data, such as regional response disparities and the underreporting of income, may affect the accuracy of the findings. Additionally, the focus on income as a proxy for poverty does not fully capture the multidimensional nature of poverty, which includes factors like access to public services, health, education, and social capital, that can also have a significant impact. These limitations suggest that future research could benefit from a more comprehensive approach, incorporating some more poverty indicators to better understand and address the issue.

Despite these challenges, the study provides valuable informations of the socioeconomic determinants of poverty in Italy and offers important implications for policy. For example, it suggests that interventions aimed at increasing educational attainment, promoting homeownership, enhancing financial inclusion and addressing regional disparities could be effective in reducing poverty and vulnerability.

Going into more detail, the suggest for the government can be represented by different key points: given the significant decrease in poverty risk associated with homeownership, policies that facilitate access to homeownership should be prioritized, expanding affordable housing programs, offering low-interest loans or subsidies for first-time homebuyers, and providing tax incentives for homeownership. In this way, it can impact by reducing the financial burden of housing, providing greater stability and security for vulnerable households. Given the strong relationship between higher education levels and substantial decreases in the likelihood of being poor, the government should focus on improving access to high-level education, particularly in disadvantaged areas of south and centre Italy. For example, this could be done increasing funding for schools, offering scholarships or grants for higher education. Given the persistent economic gap between north and south of Italy, the government should invest in targeted regional policies such as infrastructure, create job opportunities and enhance public services in the south to reduce the gap with the north. For example, it can implement policies that encourage business development, particularly in underdeveloped areas, stimulating economic growth and reduce regional inequalities. Given the significant protective effect of having a bank or postal deposit, the government should implement policies that promote financial literacy and ensure that all citizens have access to basic financial services, encouraging prudent financial management. This could include expanding access to low-cost banking services, encouraging savings through matched savings programs and offering financial education programs to teach households about budgeting, saving and managing debt. Alternatively, social safety nets, such as unemployment benefits and income support programs, should be strengthened to provide a buffer against financial shocks. Given the increased poverty risk among pensioners, reforms to the pension system are necessary to ensure that retirees have sufficient income to maintain their standard of living. This could involve adjusting pension benefits to better reflect the cost of living, particularly in regions where inflation is higher. For example, policies can encourage private savings for retirement that could help supplement public pensions.

In conclusion, this thesis contributes to the existing body of literature by providing a detailed analysis of poverty and vulnerability in Italy, offering a solid basis for future research and policy development against poverty and promoting economic stability for vulnerable populations. Another possible direction for research is the study of the vulnerability of social groups, such as dividing the sample in age group, or moreover specific social group such as divorced people. So, identifying the most significant characteristics that determine their condition of exposure to risk, government should focus public policies on the most vulnerable categories of people. In

this way, from one side, the state of deprivation of households can be alleviated, and from the other side, poverty traps and situation with high level of households at risk could be avoided.

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