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Understanding the non-take-up of the Italian Minimum Income Scheme*

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Tommaso Nannicini

Understanding the non-take-up of the Italian Minimum Income Scheme*

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Understanding the non-take-up of the Italian Minimum Income Scheme*

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Abstract

In recent years Minimum Income Schemes gained attention as policy tools aimed at providing a safety net to those that fall in poverty. Yet, much literature shows that the take up of these measures is far from being complete, posing serious challenges for policy makers. Most of the existing evidence on the determinants of low take-up comes from countries with a relatively high GDP and low unemployment, such as Anglo-Saxon, Central European and Scandinavian welfare states. In this work we provide for the first time estimates of the take-up of a Minimum Income Scheme in a Southern European welfare state using high-quality administrative data. We do this in Italy considering the case of the Citizenship Income through administrative data from the Italian National Social Security Institute (INPS). We estimate an average take-up of 61.3% in 2021. However, our estimates at the monthly and at the subnational level reveal relevant seasonal and geographical variations in take-up. While take-up tends to be higher in Southern regions, our results show a steep decrease from July 2021 onwards across all macro-areas. This might be linked to improved labour market conditions following the phasing out of the lockdown and social distancing measures introduced during the Covid-19 pandemic. Our multivariate analysis shows that household members labour market status and policy design features have a stable impact on eligibility over time, while their relationship with take-up displays significant monthly variations. Finally, our analysis reveals that the design of this policy significantly favoured single-person households.

Keywords: non-take-up; poverty; minimum income scheme; administrative data; social transfers.

JEL codes: C15; I30; I38.

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Comprendere il non-take-up del Reddito di Cittadinanza*

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Abstract

Negli ultimi anni c'è stata un'attenzione crescente alle misure di reddito minimo come strumenti di policy volti a supportare chi cade in povertà. Tuttavia, molti studi dimostrano che il take up di queste misure è ben lungi dall'essere completo, rappresentando un problema importante per i decisori pubblici. Inoltre, la maggior parte delle ricerche su questo tema è stata realizzata in paesi con un PIL relativamente elevato e bassa disoccupazione, come quelli anglosassoni, dell'Europa centrale e scandinavi. In questo lavoro forniamo per la prima volta stime sul take up di un programma di reddito minimo in un paese dell'Europa meridionale utilizzando dati amministrativi di elevata qualità. Lo facciamo in Italia considerando il caso del Reddito di Cittadinanza attraverso i dati amministrativi dell'Istituto Nazionale della Previdenza Sociale (INPS). Stimiamo un take up medio del 61,3% nel 2021. Tuttavia, le nostre stime a livello mensile e per macroarea rivelano rilevanti variazioni stagionali e geografiche. Mentre il take up tende a essere più elevato nelle regioni meridionali, i nostri risultati mostrano una forte diminuzione a partire da luglio 2021 in tutte le macroaree. Questo potrebbe essere legato al miglioramento delle condizioni del mercato del lavoro in seguito alla graduale eliminazione delle misure di lockdown e di distanziamento sociale introdotte durante la pandemia Covid-19. La nostra analisi multivariata mostra che lo status lavorativo dei membri del nucleo familiare e i requisiti della misura hanno una correlazione stabile con l'eleggibilità nel tempo, mentre la loro correlazione con il take up mostra significative variazioni mensili. Infine, la nostra analisi rivela che il disegno di questa politica ha favorito in modo significativo i nuclei monocomponente.

Parole chiave: non-take-up; povertà; misura di reddito minimo; dati amministrativi; trasferimenti sociali.

Codici JEL: C15; I30; I38.

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1. Introduction

A growing body of literature shows that a significant proportion of those potentially eligible to income support measures do not receive them (Immervol et al. 2014; Currie 2004; Riphahn 2001; Bruckmeier and Wiemers 2012; Van Oorschot 1991; Bargain et al. 2012; Bhargava and Manoli 2015, Hernanz et al. 2004, Ko and Moffit 2022). This phenomenon, known as 'incomplete welfare take-up,' refers to the proportion of eligible individuals who do not receive welfare. Paradoxically, those with the greatest need should access support more easily, yet they often do not. In recent years, the incomplete take-up of Minimum Income Schemes (MIS henceforth) has increasingly been in the spotlight (Riphahn 2001; Bargain et al. 2012; Fuchs et al. 2020; Almeida et al. 2022; Goedemé et al. 2022; Marc et al. 2022). MIS represent one of the pillars of the European Social Rights Action Plan, aimed at ensuring that those without sufficient resources have the right to a minimum standard of life (European Commission 2017). Considering their central role for those most disadvantaged, being able to quantify and understand incomplete take-up of MIS is of great relevance both for academics and policy makers.

However, previous literature has highlighted the complexity of estimating welfare take-up, that requires the identification of both welfare beneficiaries and the pool of those eligible. Therefore, it is essential to have detailed and representative individual and household level data. So far estimates of take up have been conducted using microsimulation models that employ either survey data, administrative data or survey data linked with administrative sources (Goedemé and Jassen 2020). While the use of administrative data sources in recent years has greatly improved the quality of the available estimates (Hernanz et al. 2004; Department of Work and Pensions 2016; Fuchs et al. 2020; Bruckmeier et al. 2021; Goedemé et al. 2022; Bargain et al. 2012; Iselin et al. 2023), these are often available only for a subset of countries belonging mostly to Anglo-Saxon (Hernanz et al. 2004; Department of Work and Pensions 2016; Iselin et al. 2023), Central European (Fuchs et al. 2020; Bruckmeier et al. 2021; Goedemé et al. 2022; DREES 2022) and Scandinavian welfare states (Bargain et al. 2012).

The few available studies on Southern European countries are based on national household surveys (Gallo and Raitano 2020) or on a mix of survey and administrative data (Matsaganis et al. 2010). Furthermore, estimates of non-take-up are available for Spain and Greece only for means-tested retirement benefits (Matsaganis et al. 2010), leaving out the working age population that is a typical target of universal MISs (Raitano et al. 2021). More recently, Gallo and Raitano (2020) used household survey data to estimate the take up of a MIS in Italy.

However, estimating take up through survey data poses several methodological challenges. First, welfare stigma could induce beneficiaries to underreport welfare use in surveys (Moffit 1983), and this might lead to underestimate take-up. Second, nationally representative surveys usually capture only a small sub-sample of low-income households and welfare recipients, limiting further analyses of the determinants of take-up (Goedemé and Jassen 2020; Raitano et al. 2021).

The scarcity of studies on the non-take up of MIS in Southern Europe in part reflects the fact that these measures are relatively recent in these countries, where most means-tested payments are directed to specific categories (e.g., elderly, disabled) (Saraceno 2021). Yet, this is striking if we consider that Southern European countries are precisely those that would benefit more from measuring non-take-up and fine-tuning their policies accordingly. They are in fact characterized by much higher poverty rates and sluggish economic growth compared to other advanced economies (Michálek & Výbošťok 2019). Moreover, findings from other welfare states might be difficult to generalize to Southern European ones, that are characterized by a greater importance of family support networks and underdeveloped administrative capacity (Ferrera 1996; Ferrera 2005; Natili 2019; Saraceno et al. 2022) – all factors that might impact take-up (Van Oorschoot 1991).

In this work we contribute to the literature by estimating for the first time the take-up of a MIS in a Southern European welfare state using high quality administrative data. We do this considering the case of the Italian MIS that was active in years 2019-2023. We use administrative data from 2021 gathered by the Italian National Social Security Institute (INPS). This is the same dataset used by the public administration to assess eligibility, making it the most detailed and accurate source for official income and asset assessments. Compared to previous studies we improve on the degree of disaggregation of results and go beyond the estimation of country-level and yearly take-up rates.

Our data is geographically fine-grained enough to estimate take-up at both national and subnational levels. This is very relevant in the Italian context, where there are large geographical variations in the distribution of poverty and administrative capacity (Salvati et al. 2016; Bernini et al. 2024; Milio 2007), that in turn can affect access to welfare. Moreover, survey data are typically not suitable for this objective given the reduced sample size and limited information about respondents' geographical location.

From a temporal perspective, we can calculate monthly take-up rather than just yearly take-up, which is often the only measure available in previous studies (Matsaganis et al. 2010; Bargain et al. 2012; Fuchs et al. 2020). We evaluate eligibility and estimate the take-up using the same time frame adopted by the public administration, that in Italy decides whether to grant, suspend or approve the receipt of MIS on a monthly basis. We mimic as closely as possible the real process of deployment of the benefit, as to make our estimates of take-up realistic and meaningful. At the same time, focusing on a monthly time-frame reveals the take-up short-term reactions to the economic cycle, that are obscured in yearly analyses. To better observe this, we consider the monthly take up in year 2021, that was characterized by sharp fluctuations of GDP and occupation due to the gradual phasing out of the Covid-19 mobility restrictions (Istat 2022).

Finally, following the theoretical model of Van Oorschoot (1996) and its extensions (Janssens and Van Mechelen 2022), we study the determinants of take-up considering household level characteristics, policy design, and contextual characteristics of the area where households live. INPS administrative data contains detailed information on individual and household characteristics, as well as variables used for all the income and asset tests embedded in the MIS policy. We link our rich administrative microdata with aggregate information at the municipal and provincial level. By doing this we control for several characteristics of the place of residence that might contribute to explain take-up (e.g., the presence of other claimants, employment level, prevalence of workers in low-wage sectors).

The remainder of the paper is organised as follows. Section 2 presents the Italian context and the MIS object of this study. Section 3 describes the administrative datasets and the methodology adopted to estimate the take-up, while Section 4 illustrates the estimation strategy for the analysis of take up. Section 5 shows first some descriptive evidence and then the results of the econometric analysis. The last section concludes and discusses policy implications stemming from the analysis.

2. The Italian Minimum Income Scheme

In recent years Italy has undergone dramatic policy reforms in the area of income support measures. It was the last country in the European Union to introduce a MIS covering the work-age population (Raitano et al. 2021), after decades of experimentation at the local level and cyclical policy retrenchments (Natili 2019; Gallo 2021). The first universal MIS was introduced in 2018 under the name Inclusion Income (*Reddito di Inclusione*). This payment was then replaced in 2019 by a more generous scheme named Citizenship Income (*Reddito di Cittadinanza*). This measure remained active until 2023[3]. The Citizenship Income has represented the first attempt to provide a universal and relatively generous safety net in Italy (Saraceno et al. 2022), in line with other advanced welfare states. In this work we focus on estimating the take-up of the Italian Citizenship Income. Hereafter, we refer to it as the Minimum Income Scheme (MIS) for consistency with international definitions.

We estimate the take up of MIS in 2021. This represents the ideal year to study the take-up of the MIS in Italy for two main reasons. First, at this time a few years had passed from the policy initial implementation, while still being soon enough before its retrenchment. Therefore, we can expect that during 2021 the take up should have reached its maximum. Second, the year 2021 has been featured by recessive effects due to lasting pandemic-related restrictive measures during the first months of the year

[3] In January 2024 the Citizenship income was replaced by two categorical measures, the Inclusion Allowance (Assegno di Inclusione) and Support for Training and Work (Supporto per la Formazione e Lavoro). While the former is directed to specific categories among the poor (elderly, disabled, with care duties or in charge of young children), the latter is an allowance to participate in activation programs directed to the working age population.

and a sharp economic recovery (Istat 2022). The latter feature is particularly important as it allows to observe short-term reactions of MIS take-up to fluctuations in the economic cycle.

As showed in Figure 1, the number of beneficiaries was at its highest during 2021, peaking in June at around 1.35 million recipient households.[4] The high number of recipients in 2021 is unsurprising, considering that at that point in time this policy was in its third year, and following strong public debate it was relatively well known, even among vulnerable segments of the population (Gatta 2023). At the same time, Italy was recovering from the economic shock generated by the Covid-19 pandemic in the previous year, when this measure might have represented an important support for many that lost their jobs.

<Figure 1 about here>

Similarly to other MISs across Europe, the Italian one presented both tight income and asset tests. The thresholds for eligibility depended on family composition and were based on an equivalence scale that accounts for the presence of additional household members. In Table 1 we summarize the main features of this policy considering the case of a single person, that are described in detail in what follows.[5]

In terms of income targeting, the eligibility criteria required an yearly household income below 9,360 euros for those renting a place, and below 6,000 euros if not. Average yearly household savings needed to be below 6,000 euros and it was possible to own real estate only up to a value of 30,000 euros, excluding the home of residence.

Additionally, households had to pass a means-test conducted using the ISEE (*Indicatore della Situazione Economica Equivalente*),[6] an indicator of family economic condition used in the Italian welfare system to establish eligibility to a number of provisions (Boscolo and Gallo 2023). All families applying for means-tested benefits – including the MIS - have to submit first an ISEE declaration, where they indicate their family composition, income and assets. The data collected through the ISEE declaration is then used to calculate an equivalized indicator of household resources, corrected considering the number and characteristics of family members (e.g., disabled, children). Importantly, households had to have an ISEE indicator below 9,360 euros to be eligible to the MIS.

In terms of residency requirements, this benefit had one of the strictest in Europe (Saraceno et al. 2022). Eligibility was limited to claimants that had been resident in Italy for at least 10 years, of which

[4] The steep increase in the share of new entrants at the end of 2020 is instead in line with the fact that benefit receipt was interrupted for one month every 18 months. Since this policy was first rolled out in April 2019, the first block of interruptions happened precisely in October 2020. The new entrants in the following months represent both new and previous recipients that had to reapply to receive the measure.

[5] For more details about this policy interested readers can refer to Raitano et al. (2021:90-93).

[6] The ISEE is a complex indicator combining household income and wealth. It consists of the sum of the household income and 20% of the household wealth (in terms of both financial assets and property) divided by an ad hoc equivalence scale. The ISEE equivalence scale is equal to the number of household members raised to the power 0.65.

the last two continuous. Moreover, the claimant had to be either an EU citizen, a non-EU citizen with a long-term resident permit or an asylum seeker. Finally, eligibility for the MIS depended also on criminal record and ownership of certain durable goods (e.g., new cars or motorbikes above a certain dimension or boats). Information about these aspects was not available for households that never applied for MIS, and therefore we could not simulate these requirements. Nevertheless, it is expected that these criteria represented a cause of ineligibility only for a minimal fraction of the applicants. As a result, this omission is unlikely to impact significantly our estimates of take-up.

<Table 1 about here>

Finally, the amount of the MIS was calculated as the difference between the income threshold and the income of the beneficiary. Thus, a single person with null income received 6,000 euros per year, that is 500 euros per month. Moreover, top ups were available to reimburse the expenses of living in a rented accommodation or paying a mortgage, respectively up to 3,360 euros and 1,800 euros per year. Overall, if we consider also the rental component, a single person could receive up to 9,360 euros per year, corresponding to 780 euros per month. Figure 2 displays the distribution of the monthly amounts of the MIS. There is a spike at 500 euros per month, that is the amount for a single claimant not renting an accommodation.

<Figure 2 about here>

3. Data and estimation of take-up

In this work we use INPS administrative data to study the take-up of the Italian MIS. The estimates are based on two data sources. The first is the ISEE archive 2021, that contains detailed information on family composition, income and assets of the universe of households that filed an ISEE declaration in 2021. From this archive we extracted the universe of households that were assigned an ISEE value lower than 9,360 euros. In what follows we will refer to this data source as the “reduced ISEE archive”. Households with an ISEE value above this threshold are ineligible to the MIS, thus we have excluded them at the start of the study.

As mentioned earlier, in Italy households have to submit an ISEE declaration to receive a wide variety of benefits. Even though some of these households might file an ISEE declaration, they might do it for reasons unrelated to applying for cash transfers, given the many different situations in which this document might be required.[7] Through a microsimulation we identified the households eligible to MIS among those in the reduced ISEE archive. We could achieve this using the variables available in the ISEE archive, which closely mirror those used by INPS to determine a claimant's eligibility for MIS. The ISEE declaration is one of the documents required to apply for the MIS and the income and assets reported in there are used as a base for further means-testing.

The reduced ISEE archive was then linked with the second data source, that is the MIS archive. This dataset contains detailed microdata on the households that ever applied or received the MIS from April 2019 to February 2022. By linking the reduced ISEE archive and the MIS archive, we could identify among the eligible households those that received the measure and those that did not, month by month. We then calculated the monthly take-up.

MIS claimant households had to renew their ISEE declaration by the end of January each year to receive the payment in the next 12 months. This means that in January 2021 some households were still recipients based on an ISEE declaration filed in 2020. Similarly in January 2022 some households might have still been recipients based on an ISEE declaration filed in 2021. To account for this mismatch, the take-up analysis presented here runs from February 2021 to January 2022. Table A1 in the Appendix provides the descriptive statistics of the household in the reduced ISEE archive for selected months.

4. Estimation strategy for the analysis of take-up

In section 5.2 we use multivariate linear probability models to study the determinants of take-up among households classified as eligible by our microsimulation. We compute monthly regressions to unpack seasonality in the relationship between take-up and its determinants. For brevity, we show results for the months of March, July and December 2021, when the take-up at the national level reaches respectively its maximum, a turning point, and its minimum (Figure 3a). For the definition of the model specification, we follow the framework of Van Oorschot (1991;1996) and its update by Janssen and Van Mechelen (2022), adapted to the Italian case. We consider three groups of determinants: (1) household variables, (2) policy design variables, and (3) context-level variables.

In the first group we consider the *household*, rather than the individual level, for two reasons. The first is that MIS is a household-based welfare provision. The second is due to the historical relevance of the family as a source of support in Italy (Ferrera 2005; Saraceno 2016; Saraceno et al. 2022), that might complement or substitute welfare use. To assess the degree of long- and short-term state dependence among households we introduce two dummies. The first takes value 1 if the household received the MIS

[7] The ISEE declaration is required for a considerable number of benefits and services provided by the Italian welfare system like new-born benefits, universal family allowances, exemption or reduction of tuition fees, university scholarships, access to homecare support, and essential services.

in year 2019 and 2020, while the second takes value 1 if the household received the MIS the month before. We include the socio-demographic characteristics of the household head, such as gender, age and nationality. Gender and age might affect the perception of stigma, since usually women and older people are considered more deserving of public support (Coughlin 1980; Van Oorschot and Roosma 2015). At the same time foreigners might have less access to information about welfare payments due to linguistic barriers. The presence of children might decrease perceived stigma and motivate household heads to apply for welfare (Riphahn 2001). At the same time the labour force status of family members might influence the appeal of applying for welfare, as income from work might represent a more attractive alternative (Bargain et al. 2012).

We consider the role of *policy design* by observing how the multiple layers of means-testing and targeting select the eligible population and lead to the observed take-up. The degree of targeting substantially affects the accessibility of welfare payments (Van Oorschot 2002; Fuchs et al. 2020; Gatta 2023). Thanks to INPS administrative data, in this work we are able to observe the correlation of take-up with income, assets and other determinants of eligibility with unprecedented precision. Moreover, we estimate MIS amount and include this as a relevant determinant of take-up. Previous literature has pointed to the importance of benefit generosity as a positive incentive to apply for welfare (Riphahn 2001; Bruckmeier and Wiemers 2012; Arrighi et al. 2015), thus representing a core characteristic of policy design in influencing the take-up rate.

Finally, we study the impact on the take-up of the *context* where claimant household live by exploiting the wide geographical variation in social and economic factors across the Italian territory. From North to South, Italy displays an impressive variation in labour market conditions, poverty, level of education, and in the quality of local institutions (Salvati et al. 2016; Bernini et al. 2024; Milio 2007), that can greatly affect access to welfare (Van Oorschot 2002). We are able to account for these factors through variables that capture these contextual aspects at the provincial or municipal level. These variables come from a variety of external sources, as indicated in Table A2. We linked them to the reduced ISEE archive using information on the geographic location of households.

The proposed econometric analysis is complemented by linear probability models exploring the determinants of eligibility (Figure A1) and claimant status (Figure A2) among the full universe of households with an ISEE below 9,360 euros. The results for these latter models are available in the Appendix.

Finally, we conduct additional analyses to provide more context to the results of the linear probability models. In section 5.3 we compute the Owen value decomposition (Owen 1977; Shapley 1953) and show the relative contribution of each block of variables in explaining the take up among those eligible. In section 5.4 we use a multinomial logit to study how household, policy design and contextual variables contribute to classify households into (1) non-eligible non-recipient households, (2) eligible non-recipient households and (3) eligible recipient households. This comparison provides more information on the factors that characterize these three groups, and reveal potential policy levers for increasing take up. In section 5.5 we conclude the empirical analysis by conducting heterogeneity analysis. First, we replicated the linear probability model predicting take up for the subsample of single-person households. Given the important heterogeneity across the Italian territory (Salvati et al. 2016; Bernini et al. 2024; Milio 2007), we also conducted the linear probability models separately for households in Northern, Central, and Southern regions.

5. Results

5.1. Estimating the take-up of the Italian Minimum Income Scheme

Table 2 provides some additional context by showing the estimate of eligible households and the take-up of MIS from 2019, the year it was introduced, to 2021. For years 2019 and 2020, estimates are made through microsimulations on a version of the Italian component of the EU-SILC 2017 survey data merged with income administrative registers (Gallo and Raitano 2020), while for 2021 they are based exclusively on INPS administrative data. In 2019 the estimated take-up is 61.3%, with a pool of eligible households of about 1.8 million, and about 1.1 million recipient households. In 2020 the number of eligible household remained stable overall,while the number of recipients reached 1.3 million households, leading to a take up of 73.4%. In 2021, using INPS administrative data, we estimated around 2 million eligible households, while the number of recipient households remained similar to that in 2020. This resulted in a take up of 61.3%, lower than the one in 2020 and similar to the one in 2019.

This difference in take-up between 2020 and 2021 can be traced to two possible explanations. On one hand, the survey data adopted by Gallo and Raitano (2020), although subjected to techniques to consider changes in employment conditions and access to social and emergency transfers for households in 2020, may not fully capture the increase in poverty among households that occurred as a result of the Covid-19 pandemic. On the other hand, with the introduction of the MIS and the Covid-19 Emergency Income (Reddito di Emergenza) in 2019 and 2020–2021, along with the worsening economic situation for some groups, more low-income households may have submitted an ISEE declaration for the first time. This means that over time the ISEE archive became more representative of a broader set of the population.

<Table 2 about here>

It is important to note that even the take-up estimates obtained through the INPS administrative data probably overestimates the true take-up. On one hand the pandemic and the Covid-19 measures may have increased the number of disadvantaged households among those submitting an ISEE declaration. On the other hand, INPS administrative data may exclude a certain number of households that - although in financial hardship - for some reason did not submit an ISEE declaration (Boscolo and Gallo 2023). Therefore, the estimate presented here for 2021 is to be considered an upper limit to the actual take-up. Bearing in mind that the take-up for similar measures is between 20 and 75 among EU countries (Dubois and Ludwinek 2015), the MIS in Italy has reached a relatively large pool of eligible households in Italy.

Figure 3a shows the evolution of take-up from February 2021 to January 2022 in Italy and its macro-areas. The first interesting element is the seasonality of take-up, which peaks at around 66.8% in March 2021 at the national level, and then declines in the following months. While take-up by macro-area follows a similar trend, we observe marked differences in the level of take-up across macro-areas. In particular, the highest take-up is recorded in the South and Islands, where it reaches a maximum of 71.8% in March 2021 and a minimum of 61.7% in November 2021. In contrast, the lowest take-up is in the North-Eastern regions, where the highest take-up is 53.8% in April 2021 and the lowest is 44.2% in December 2021. This patter is further confirmed at a more granular level, when we plot the take up at the municipal level (Figure 3b) and for four main Italian cities (Figure A3). The take up tends to be lower in municipalities located in the North-East of the country already in March 2021, and this becomes even more evident in December 2021. These differences reflect a higher incidence of absolute poverty in the South, which could somewhat mitigate the phenomenon of social stigma and increase the diffusion of welfare policies. The presence of better job opportunities in the North, which can represent an alternative to the MIS, can explain a lower take up in Northern areas.

<Figure 3a and 3b about here>

The change in take-up observed in Figures 3a and 3b could be due to two factors. The first is the economic recovery that has taken place in the second half of 2021, when all Covid-19-related mobility restrictions were removed (Istat 2022). In that period, more household members might have started working again. This may have increased both the number of households no longer eligible for MIS and the households that - although still eligible - may have changed plans after claiming and preferred to work as an alternative to the measure. Second, new households with ISEE below 9,360 euros might have entered the ISEE archive in the second half of the year. Families tend to submit their ISEE declaration for university and education-related exemptions in the summer months, in preparation for the academic year. Moreover, a preliminary version of a new family allowance policy (*Assegno Unico*) was introduced in July 2021 (fully in place from March 2022), targeting a wide range of households. This might have further expanded the number of households submitting an ISEE declaration.

To better understand which of these two factors might be driving the downward trend observed in Figure 1, in Figure 4 we analyse the components of the take-up at the national level. Between February

2021 and January 2022 both the percentage of eligible and of recipient households decreased. However, starting from July 2021 the proportion of recipient households started decreasing faster than that of those eligible, generating the shape of the take-up curve showed in Figure 1. Moreover, there is a sharp increase over time in the proportion of ineligible households. Figure 5 shows that income-testing seems to be the most relevant cause of ineligibility across all the months considered, while other requirements do not matter as much. The documented increase in the proportion of households ineligible due to violation of income requirements further suggests that recovering labour markets maybe be driving the observed trend in take-up. Therefore, it is plausible that economic growth might have promoted the exit of former recipients from the measure at a higher rate compared to the entry of new eligible applicants, resulting in an overall decrease in take-up.

<Figure 4 about here>

<Figure 5 about here>

However, it could still be that the observed decreasing trend in take-up was driven by the entry in the ISEE archive of families with children that submitted an ISEE declaration for other purposes (e.g., receiving education-related exemptions, family benefits, etc.), that are relatively better off than MIS applicants. To test this hypothesis, in Figure 6 we compute the take-up by household type. We observe a decrease in take-up for all households, including for singles and those without children. At the same time, this drop is sharper for families with children, that are those most likely to submit an ISEE declaration also for other purposes rather than applying for MIS. Overall, the evidence presented suggests that, while the entry of new households in the ISEE archive might play a role, still the decrease in take-up in the second half of the year seems to be mainly driven by improved economic and labour market conditions.

<Figure 6 about here>

5.2. The determinants of eligibility and take-up

In this section we describe the results of the linear probability model predicting take up of the MIS. Given the large number of independent variables, we present the same linear probability model subdivided across three figures. In Figure 7 we plot the coefficients of the two dummies related to previous benefit receipt, while in Figure 8 we plot the coefficients related to household and policy design variables. Finally, in Figure 9 we plot the coefficients related to the local context.

The household level

The first noticeable element is the role of previous MIS receipt for future receipt. Figure 7 shows that recipient families in years 2019 and 2020 have a much higher probability of being recipient also in 2021 ($p<0.01$ in all the months). However, large coefficients are concentrated at the beginning of the year, and become progressively smaller after May 2021. On the contrary, the coefficient of having been a recipient in the previous month has a small size at the beginning of the year, but becomes the main predictor of receipt from May 2021 onwards ($p<0.01$ in all the months). This could be the result of the mechanism used by INPS for benefit award. While at the beginning of the year this is based on the ISEE declaration, during the year continuation of receipt is established by a system of monthly checks, that update the situation of the claimant based on information gathered during the previous month.

<Figure 7 about here>

When we look at other household level characteristics, household type is the predictor that stands out. Figure 8 shows that compared to singles, all the other household typologies have a lower chance of take-up of MIS, and in particular households with children. This pattern is strongest in March 2021 and July 2021 (except for families with two adults only) and it reduces in December 2021. Interestingly, when we look at the determinants of eligibility, we find the opposite pattern. Single households are the least likely to be eligible (Figure A1(a)), but they are more likely to claim compared to other types of households with children (Figure A2(a)). This contributes to increasing their chances of take-up, as showed in Figure 8.

The presence within a household of members with a permanent contract has a strong negative and statistically significant association with receipt throughout the year ($p<0.01$ in all months in Figure 8), that reaches its maximum in July 2021, when it reduces the probability of receipt by 6 percentage points. However, the presence of household members with a permanent contract does not predict eligibility (Figure A1(a)), but it is negatively correlated with claiming behavior (Figure A2(a)). This contributes to explaining the negative selection of households with permanent workers among recipients. They are less propense to apply even though they are as likely to be eligible as other households with ISEE below 9,360 euros.

The policy design level

We now turn to policy design variables, such as income, wealth, type of dwelling and benefit amount. We observe that household income displays a different association with MIS eligibility and receipt. Figure A1(a) shows that while the probability of being eligible decreases as income rises, this relationship is not as stable when it comes to predicting receipt. Households in the 2nd income quartile are the least likely to take-up the MIS in March 2021 (Figure 8). However, those in the 4^{th} income quartile become least likely to take-up the measure in July 2021, while the relationship between income and MIS almost disappears in December 2021. This inconsistency could be related to a tension between Mattew effects (Cantillon 2011; Bonoli, Cantillon and Van Lancker 2017), and the targeting criteria. While Mattew effects make accessing public resources more likely for better off households – for example because they have better access to information – targeting criteria drive households with incomes close to the ineligibility threshold out of the scheme.

The type of dwelling displays a significant association with take up (Figure 8). This is unsurprising, as the type of dwelling influences both means-testing rules and the amount of MIS paid to households. As highlighted in Table 1, households that live in rented accommodation benefit from a higher threshold for income-testing compared to homeowners. Moreover, households that rent or have a mortgage are eligible to receive an additional top up payment. Figure A1(a) shows that renting households are more likely to be eligible to the MIS ($p<0.01$ for all months). Yet, Figure 8 shows relevant monthly variations in the relationship between dwelling type and MIS receipt. All other accommodation types increase the probability of receipt compared to home ownership. However, while having a mortgage increases the probability of receipt in March 2021 ($p<0.01$), the magnitude of the coefficient decreases over time. Renting households are significantly more likely than homeowners to be MIS recipients in July 2021 ($p<0.01$), but the coefficient becomes substantively large in December 2021. This could be attributed to the rebound of the rental market post-covid (OMI 2022). Upwards pressures on the rentals might have convinced a larger number of potential recipients to apply for the measure. Models in Figure A2(a) support this hypothesis, as they show an increasingly positive relationship between being a renting household and applying for the MIS over time.

Finally, the literature has showed that benefit generosity is an important policy design element, that strongly influences welfare take-up (Riphahn 2001; Bruckmeier and Wiemers 2012; Arrighi et al. 2015). Therefore, based on our microsimulation model, we computed the predicted benefit entitlement and added it as an independent variable in our linear probability model. Results show that receipt is positively associated with benefit amount, but this effect is sharp only in March, while it fades in July and becomes slightly negative in December (Figure 8). This may be linked to the fact that most households enter the program at the beginning of the year, when the estimated benefit amount is likely to play a significant role.

<Figure 8 about here>

The context level

Finally, we focus on context level variables, that describe the area where households are located through variables either at the municipal, provincial or regional level. After controlling for household level variables and for factors that affect the policy design, only few contextual variables appear to affect MIS receipt (Figure 9) and eligibility (Figure A2(b)). Moreover, their coefficients display significant heterogeneity over time. The proportion of eligible in the same municipality seems to positively predict take up in March, but the effect becomes smaller or null in the following months.

In the regressions we included an index measuring the quality of institutions at the local level, as we predict this to have an impact on the delivery of public services (Van Oorschoot 1991), such as welfare provisions. However, in Figure 9 we find a slight negative correlation between quality of local institutions and take-up, which is statistically significant only in July 2021. This suggests that households living in areas with high institutional quality might be able to access other forms of support that reduce the need to apply for MIS. Relatedly, we observe that the institutional quality index does not affect eligibility (Figure A1(b)) and it is slightly negatively correlated with claiming behavior (Figure A2(b)).

As expected, the employment rate at the local level is negatively correlated with take-up (Figure 9) and eligibility (Figure A2(b)) across the three months considered. The availability of employment opportunities might reduce the need to rely on welfare payments. However, if jobs are concentrated in low-wage sectors, workers might still need to complement their salaries with welfare payments. Therefore, we introduce two variables at the local level that measure the share of workers in construction and hospitality, where low-wage jobs tend to be more common (Osterman 2020).

The share of workers in construction negatively predicts take up only in March, while it does not affect eligibility (Figure A2(a)) or claiming behavior (Figure A3(b)). Therefore, the prevalence of this sector among those employed does not seem to promote the take up of MIS. On the other hand, the share of workers in hospitality (e.g., hotel and restaurants) correlates positively with take up in March 2021, and then it displays a negative correlation in July and December 2021 (Figure 9). This is consistent with the cycle of the tourism sector, that reaches its peaks during the summer and the Christmas holiday seasons. During peak seasons more households might choose to work in hospitality rather than being on welfare, leading to a decrease in take-up, while they might rely on welfare during low season. At the same time, this variable displays a positive significant correlation with eligibility for all three months (Figure A2(b)). This suggests that jobs in hospitality might provide insufficient economic security, increasing the pool of households potentially eligible to MIS.

Finally, other contextual variables (e.g., income share ratio, education-related variables, export, share of workers in sectors affected by the lockdowns) do not seem to have a stable relationship with take up, or coefficients are imprecisely estimated.

As a general remark, we observe much more time-variability for the coefficients in the model predicting take up (Figure 9), compared to those in the models predicting eligibility (Figure A2(b)). Together with the results presented above, this points to the relevance of economic fluctuations and seasonality as important aspects of welfare take up.

<Figure 9 about here>

5.3 Owen value decomposition

In this section we complement the regression analysis in Figures 8 and 9 by looking at the relative contribution of each group of variables in explaining the take-up of Minimum Income Scheme. We do this through the Shapley decomposition (Shapley 1953), that we use to compute the share of the R-squared explained by each variable in the linear probability models in Figures 8 and 9. We considered six groups of variables: (1) previous MIS use, (2) household head characteristics, (3) household characteristics, (4) policy design variables, (5) contextual variables, (6) regional fixed effects. To analyse the explanatory power of each of these groups of variables we adopt the Owen value (Owen 1977), that is a generalization of the Shapley decomposition.

The results in Table 3 show that previous MIS use (in year 2019/2020 or in the previous month) contributes to explain about 88% of the variance in take-up, irrespective of the months considered. This suggests significant time-dependence in welfare use. However, this is somewhat unsurprising considering that this benefit once awarded was paid for 18 months, with interruptions occurring only in case of anomalies arising during the monthly controls carried out by the public administration on beneficiaries.

When we look at other groups of variables, their explanatory power displays significant variability over time. In March 2021 policy design variables are those that make the second-largest contribution to explaining take-up, explaining 4.53% of the R-squared. In July and December 2021, household characteristics are the most relevant group of variables, explaining respectively 5.45% and 4.97% of the R-squared in these two months. This evidence suggests that at the beginning of the year, when most people file a new ISEE declaration, policy design elements are those that matter the most for take-up. However, during the rest of the year household characteristics and employment decisions become more relevant in explaining take-up. This is in line with the evidence showed in paragraph 5.1, suggesting an increased exit from the measure due to improved labour market and economic conditions post-Covid. Finally, household head characteristics, contextual variables and regional fixed effects have a comparatively small explanatory power compared to the other groups of variables described above.

<Table 3 about here>

5.4 Multinomial logit analysis

In this section we turn to studying which determinants are most important in classifying households into three main groups: (1) non-eligible non-recipient households, (2) eligible non-recipient households and (3) eligible recipient households. We do this through a multinomial logit where non-eligible non-recipient households are the reference category. Results are reported in Table 4 for the month of March 2021 (results for other months are available upon request).

Households whose head is a woman, or made of components that are all older than 67 have a positive probability of being eligible. However, the log-odds tend to be larger for eligible non-recipients than eligible recipients. Most household types have a higher probability of being eligible non-recipients than recipients, compared to those single, with the exception of adults with three or more children.

Interestingly households with at least one permanent or temporary worker are more likely to be eligible non-recipients, but less likely to be eligible recipients, compared to being non-eligible non-recipients. This could be related to the presence of households with working-poor members that prefer staying in employment rather than receiving the MIS, even though they are potentially eligible. At the same time, households with working members are less likely to be eligible recipients, as they could easily go above the income thresholds for eligibility through fluctuations of their work-related earnings. Relatedly, the presence of unemployed members within the household increases the probability of being an eligible non-recipient household, and drives up even more the probability of being an eligible recipient household.

As expected, variables that are used for means-testing as part of the policy design of MIS, such as income and savings, have a negative relationship with the probability of being both eligible recipient and non-recipient. Similarly, compared to homeowners, renting households are more likely to be eligible non-recipients, and even more to be eligible recipients. This is in line with the higher income threshold for those renting, as pointed out in Table 1.

When we look at contextual variables, it is interesting to notice a positive relationship between the proportion of eligible in the municipality and the probability of being eligible, both recipient and non-recipient. This positive correlation is strongest when predicting being an eligible recipient household. Finally, while a higher employment rate reduces the probability of being eligible (both non-recipient and recipient), the share of workers in hospitality displays positive and significant coefficients. Together with the results from the linear probability model, these findings further suggest that in areas where employment in low wage sectors is widespread, households might have fewer decent employment options. As a result, they might be more likely to be working-poor and become eligible (either recipient or non-recipient).

<Table 4 about here>

5.5 Heterogeneity analysis

In section 5.1 we observed that the take-up varies significantly by geographic areas (Figure 3a and 3b) and household type (Figure 6). In this section we explore whether there are significant differences in the relationship between take-up and its determinants, depending on household composition and macro-area. We run linear probability models as per Figure 8 and 9 on single-person households only (Table A3), and on households living in Northern (Table A4), Central (Table A5) and Southern (Table A6) regions of Italy. The full tables of results are available in the Appendix.

Single-person households are those that display the most heterogenous behaviour. While in the baseline model the presence of unemployed household members positively predicts take-up, this variable either displays a negative or null coefficient among singles. Moreover, for singles the results are substantially reversed when we look at policy design variables. Among this subgroup, the higher the household income, the more likely is take-up. Moreover, single households paying rent tend to be less likely to be recipients than homeowners. Benefit amount strongly and positively predicts take-up in all the three months, while in the baseline specification this effect fades or tends to become negative over time. These differences are likely to be driven by the design of the MIS, that was characterized by an equivalence scale that favored single households both in terms of eligibility and benefit amount (Italian Ministry of Work 2021).

When we look at the linear probability models by macro-area, the estimates are similar to those in the baseline, with a few exceptions. Compared to households in other regions, for those in Southern Italy we find that the probability of take up decreases consistently as household income increases (Table A6). Moreover, we find that in the South the share of eligible households displays a larger positive correlation with take-up throughout the year. This latter finding reflects the larger concentration of poorer households in the South (Salvati et al. 2016; Bernini et al. 2024; Milio 2007), that are more likely to be eligible.

Moreover, we find that a higher share of workers in hospitality correlates negatively with take up only in July 2021 in the South (Table A6), while this happens only in December 2021 in the North (Table A4). This is consistent with July and December representing the respective peak holiday seasons in

Southern and Northen Italy, when there is greater availability of jobs in hospitality that could represent an alternative to MIS for some households.

Finally, while in Figure 9 we noted a negative relationship between institutional quality and probability of take up, in Northern Italy and Central Italy we observe respectively a U-shaped and a negative relationship in July 2021 (Table A4 and Table A5). On the contrary, we find a positive relationship between institutional quality and take up in Southern Italy (Table A6). This might be explained by differences in the provision of welfare payments at the local level. In more resource rich Northen and Central Italian regions (Bernini et al. 2024), high quality institutions might be better able to provide local-level cash benefits to their residents (Spano 2013; Gallo 2021). These can act as substitutes for the MIS, thus decreasing the probability of take up. On the other hand, in under resourced Southern Italian regions (Accetturo et al. 2024), where local-level cash benefits are less widespread and generous (Gallo 2021), higher quality institutions might be better able to facilitate access to national-level benefits, and increase the probability of take up.

6. Conclusion

In this work we estimated for the first time the non-take-up of a universal Minimum Income Scheme in a Southern European welfare state through administrative data, considering the case of Italy. The first contribution of this study is to provide estimates disaggregated at the monthly and subnational level. By looking at monthly take-up, it was possible to unpack seasonality and trends that occur throughout the year. These are related both to the macro-economic cycle and to the way benefits are administered. Moreover, our analysis provided unique insights on the synchronic dynamic of take-up across macro-areas, that in Italy are characterized by marked differences in labour market and economic outcomes (Salvati et al. 2016; Bernini et al. 2024; Milio 2007).

We calculated an average national annual take-up rate of the Italian Minimum Income Scheme of 61.3% in 2021. However, our estimates show great variability both across macro-areas and over time. The take-up tends to be larger in Southern regions, where the poverty rate is higher and the labour market provides less opportunities, whereas the lowest take-up was found in Northern regions. Moreover, the take-up displays significant seasonality in all the macro-areas. It peaks at the beginning of the year, in March-April 2021, and then it decreases steeply in July 2021. However, this does not seem to be driven by households applying less for the MIS, but rather by the increase in the exit rate of former recipient households that experienced an increase in their incomes. Coherently with this hypothesis, after July 2021 there is an increase in the number of households that are ineligible due to failure to pass the income test. This might be connected with the post-pandemic economic recovery that followed the second and third trimesters of 2021 (Istat 2022). Improved economic conditions and the lift of lockdown measures might have boosted job creation, leading some former MIS recipients to get off welfare. This result mirrors that from Bargain et al. (2012) that show a similar dynamic during years of sustained economic growth in Finland.

The second contribution of this research is to unpack the factors influencing eligibility and take-up considering three groups of determinants: at the household level, at the policy design level and contextual determinants (Van Oorschot 1996; Janssens and Van Michelen 2022). We do this accounting for monthly variations in the relevance of these factors during the year. We show two main set of findings.

First, a significant share of variation in the probability of receiving the MIS is explained by previous benefit receipt, in line with the literature on benefit dependance (Gottschalk et al. 1994; Riphahn and Wunder 2013; Königs 2014; Immervoll et al. 2014). We are able to dissect how much this depends on receipt in previous years, as opposed to receipt in the preceding month – thus differentiating between short and long-run dependance. MIS receipt in previous years was a strong predictor of benefit receipt only at the beginning of the year, while towards the middle and the end of the year benefit receipt in the previous month becomes a major predictor.

Second, factors affecting eligibility are rather stable across months, while there is much more time-variation in the factors that influence receipt. For example, having a high income reduces the chances of being eligible. At the same time we find that the relationship between income and take up is not as linear throughout the year, and it even becomes positive among single households. This could be explained by a tension between targeting criteria (Van Oorschoot 2002) and the presence of Mattew effects (Cantillon 2011; Bonoli, Cantillon and Van Lancker 2017). In other words, among households that fulfil the income requirements, for those with more resources it might be easier to access state benefits.

At the policy design level, this study confirms the importance of benefit generosity as a predictor of take-up, similarly to previous studies (Riphahn 2001; Bruckmeier and Wiemers 2012; Arrighi et al. 2015). At the same time, we show that the effect of benefit generosity is strongest at the beginning of the year, when households have to renew their ISEE declaration and have an opportunity to actively decide whether to keep receiving the MIS or not. This time of the year can be considered a 'trigger' in the framework of Van Oorschot (1991), as it prompts households to think about their current position in the welfare system and weight potential costs and benefits of (re-)enrolling. We show also that differentiating means-testing by household dwelling-type has important consequences for take-up. A policy design that favors households in a rented accommodation – such as the MIS – is better able to reach these households when rental markets pick up, and need more support.

Interestingly, single-person households have a very heterogenous response to policy design variables. Unlike the baseline model, policy design effects are reversed: higher household income increases take-up, renters are less likely to take up MIS than homeowners and benefit amount strongly predicts take-up in all three months. These results are likely due to MIS's equivalence scale, which ended up favouring singles, although this was not the original objective of this policy that was intended as a family benefit (Italian Ministry of Work 2021). This points to the relevance of the ‘unintended consequences’ of targeting rules (Van Oorschoot 2002), and to the complexity of designing targeting criteria that are simple to implement while also reaching those most in need.

Finally, we do not find a strong role for contextual variables, that do not seem to explain a relevant share of the variability of take-up. Interestingly, we find that the relationship between the quality of institutions and take up displays relevant geographic heterogeneity. Local institutions substitute national cash transfers in the North but complement them in the South, likely due to the absence of local cash transfers (Gallo 2021). Of note, the share of hospitality workers predicts higher take-up during holiday off-peak season but lower take-up in peak season, suggesting households use MIS as a seasonal safety net.

Finally, this study does not come without limitations. While we are able to use very rich data on the universe of household with ISEE below 9,360 euros, we acknowledge that this is not a perfect representation of the universe of low-income households, as some might fail to file an ISEE declaration in the first place (Boscolo and Gallo 2023). Moreover, some of the eligibility criteria for MIS required information that was not available from the ISEE archive (e.g., ownership of vehicles). Finally, due to the nature of the administrative data, we are unable to account for the impact of informal work on benefit eligibility and take up.

Despite these limitations, this study makes a novel contribution to the literature by providing take-up estimates derived from a microsimulation built on administrative data that closely mirrors the public administration’s benefit deployment process. Leveraging this detailed dataset, we highlight the importance of accounting for both geographical and seasonal variability when analysing welfare take-up. The seasonal fluctuations in take-up suggest that the timing of administrative requirements, such as the renewal of the ISEE declaration, plays a crucial role in household decisions and should be taken into account in future policy designs. Moreover, fluctuations in the economic cycle can generate sharp differences in take-up within the same year. At same time, the geographical differences in the relationship between local institutions and take-up highlight the need for regionally differentiated implementation strategies to ensure that income support measures effectively and similarly reach those most in need across the whole country. Our findings also underscore the role of household characteristics, policy design, and broader contextual factors in shaping MIS eligibility and receipt, emphasizing the need to refine targeting criteria to prevent distortions that may favor certain groups over others. Finally, we generate new evidence from a Southern European welfare state, where research on MIS remains limited despite its central role in poverty and inequality reduction (European Commission 2017). More in general, our results provide valuable insights for designing income support measures in countries characterized by sluggish economic growth as well as strong economic and institutional heterogeneity.

References

Accetturo, A., Albanese, G., De Paola, M., & Torrini, R. (2024). The North–South Gap: Economic Development and Public Intervention. *Italian Economic Journal*, 1-19.

Almeida, V., De Poli, S., & Hernández, A. (2022). *The effectiveness of Minimum Income schemes in the EU*. European Commission.

Arrighi Y., Davin B., Trannoy A., Ventelou B. (2015). The non-take-up of long-term care benefit in France: A pecuniary motive?. *Health Policy, 119*(10): 1338–1348.

Bargain, O., Immervoll, H., & Viitamäki, H. (2012). No claim, no pain. measuring the non-take-up of social assistance using register data. *The Journal of Economic Inequality*, *10* (3), 375–395.

Bernini C., Emili S., Ferrante M.R. (2024). Chapter 6: Regional disparities in the sensitivity of wellbeing to poverty measures, in C. Lenzi and V. Fedeli (eds.), *Spatial Inequalities and Wellbeing*, 136-157, Elgaronline.

Bhargava, S., & Manoli, D. (2015). Psychological frictions and the incomplete take-up of social benefits: Evidence from an irs field experiment. *American Economic Review*, *105* (11), 3489–3529.

Bonoli, G., B. Cantillon, W. Van Lancker. (2017). Social Investment and the Matthew Effect: Limits to a Strategy. In Hemerijck, A. (eds.), *The Uses of Social Investment* (pp. 66–76). Oxford: Oxford University Press.

Boscolo, S., & Gallo, G. (2023). The Struggle of Being Poor and Claimant: Evidence on the Non-Take-Up of Social Policies in Italy. *Italian Economic Journal*, 1-24.

Bruckmeier, K., & Wiemers, J. (2012). A new targeting: a new take-up? *Empirical Economics*, *43* (2), 565–580.

Bruckmeier, K., Riphahn, R. T., & Wiemers, J. (2021). Misreporting of program take-up in survey data and its consequences for measuring non-take-up: new evidence from linked administrative and survey data. *Empirical economics*, *61*, 1567-1616.

Cantillon, B. (2011). The Paradox of the Social Investment State: Growth, Employment and Poverty in the Lisbon Era. *Journal of European Social Policy, 21*(5): 432–49.

Coughlin R. (1980) *Ideology, public opinion and welfare policy; attitudes towards taxes and spending in industrial societies.* Berkely: Institute of International Studies, University of California.

Currie, J. (2004). *The take-up of social benefits* (Tech. Rep.). National Bureau of Economic Research.

Department of Work and Pensions (2016) Income-related benefits: Estimates of take-up data for financial year 2014/15. Great Britain.

DREES (2022) *Mesurer régulièrement le non-recours au RSA et à la prime d'activité : méthode et résultats*. Les Dossiers de la DREES n° 92.

Dubois, H., & Ludwinek, A. (2015). *Access to social benefits: Reducing non-take-up*. Eurofound, Publications Office of the European Union, Luxembourg.

European Commission. (2017). *The European pillar of social rights action plan.* Employment Social Affairs and Inclusion. Brussels.

Ferrera, M. (1996). The 'Southern model' of welfare in social Europe. *Journal of European social policy*, *6*(1): 17-37.

Ferrera, M. (2005). *Welfare state reform in Southern Europe. Fighting Poverty and Social Exclusion in Italy, Spain, Portugal and Greece.* London and New York: Routledge.

Fuchs, M., Gasior, K., Premrov, T., Hollan, K., & Scoppetta, A. (2020). Falling through the social safety net? Analysing non-take-up of minimum income benefit and monetary social assistance in Austria. *Social Policy & Administration*, *54*(5), 827-843.

Gallo, G. (2021). Regional support for the national government: Joint effects of minimum income schemes in Italy. *Italian Economic Journal*, *7*(1): 149-185.

Gallo, G., & Raitano, M. (2020). SOS incomes: Simulated effects of COVID-19 and emergency benefits on individual and household income distribution in Italy. *Working Paper ECINEQ 2020 566* https://www.ecineq.org/milano/WP/ECINEQ2020-566.pdf

Gatta, A. (2023). *Welfare for the truly needy? Targeting, conditionality and the non-take-up of welfare among the homeless*. In: A target on the head?: welfare targeting, conditionality and the persistence of disadvantage, Pp. 121-194. Doctoral dissertation, European University Institute.

Goedemé, T., & Janssens, J. (2020). *The concept and measurement of non-take-up: an overview, with a focus on the non-take-up of social benefits.* InGRID-2 deliverable 9.2.

Goedemé, Tim, Julie Janssens, Johannes Derboven, Raf Van Gestel, Eva Lefevere, Gerlinde Verbist, Jorik Vergauwen, Martine Vandervelden, Laurent Nisen, Stephanie Linchet, Manon Bolland, Jean-François Reynaert, Benjamin Thiry, Maritza Lopez Novella, Elise Boucq, Karel Van den Bosch, Natascha Van Mechelen and Arne Corselis (2022) *TAKE: Reducing poverty through improving the take-up of social policies. Final Report.* Brussels: Belgian Science Policy Office 2022 – 117p. (BRAIN-be - (Belgian Research Action through Interdisciplinary Networks)).

Gottschalk, P., McLanahan, S., & Sandefur, G. D. (1994). The dynamics and intergenerational transmission of poverty and welfare participation. In D. B. Grusky (eds.), *Social Stratification*: *Class, Race, And Gender In Sociological Perspective* (pp. 378-389). Routledge.

Hernanz, V., Malherbet, F., & Pellizzari, M. (2004). *Take-up of welfare benefits in OECD countries*. OECD Social: Employment and Migration Working Papers, 17.

Immervoll, H., Jenkins, S., & Königs, S. (2014). *Are recipients of social assistance 'benefit dependent'?: Concepts, measurement and results for selected countries*. OECD Publishing.

Iselin, J., Mackay, T., & Unrath, M. (2023). Measuring take-up of the California EITC with state administrative data. *Journal of Public Economics*, *227*, 105002.

Istat. (2022). *Rapporto Annuale 2022. La situazione del paese.* Istat: Rome.

Italian Ministry of Work (2021) Relazione del Comitato Scientifico per la valutazione del Reddito di Cittadinanza. Available at https://www.lavoro.gov.it/priorita/Documents/Relazione-valutazione-RdC-final.pdf

Janssens, J., & Van Mechelen, N. (2022). To take or not to take? An overview of the factors contributing to the non-take-up of public provisions. *European Journal of Social Security*, *24*(2), 95-116.

Ko, W., & Moffitt, R. A. (2022). *Take-up of social benefits* (No. w30148). National Bureau of Economic Research.

Königs, S. (2014). State dependence in social assistance benefit receipt in Germany before and after the Hartz Reforms. In Carcillo, S., Immervoll, H., Jenkins, S. P., Königs, S., & Tatsiramos, K. (eds.), *Safety Nets and Benefit Dependence* (pp. 107-150). Bingley: Emerald Group Publishing Limited.

Marc, C., Portela, M., Hannafi, C., Le Gall, R., Rode, A., & Laguérodie, S. (2022). *Non-take-up of minimum social benefits: quantification in Europe* (Doctoral dissertation, Direction de la recherche des études, de l'évaluation et des statistiques (DREES) Ministère de l'Emploi et de la Solidarité).

Matsaganis M, Levy H, Flevotomou M (2010) Non-take-up of social benefits in Greece and Spain. *Social Policy and Administration 44*(7): 827-844. doi: 10.1111/j.1467-9515.2010.00746.x

Michálek, A., & Výbošťok, J. (2019). Economic growth, inequality and poverty in the EU. *Social Indicators Research, 141*, 611-630.

Milio, S. (2007). Can Administrative Capacity Explain Differences in Regional Performances? Evidence from Structural Funds Implementation in Southern Italy. *Regional Studies, 41*(4), 429–442. https://doi.org/10.1080/00343400601120213

Moffitt, R., (1983). An economic model of welfare stigma. *American economic review*, *73* (5), 1023–1035.

Natili, M. (2019). *The politics of minimum income: Explaining path departure and policy reversal in the age of austerity*. London: Palgrave Macmillan.

Nifo, A., & Vecchione, G. (2014). Do institutions play a role in skilled migration? The case of Italy. *Regional studies, 48*(10), 1628-1649.

OMI. (2022). *Rapporto Immobiliare 2022. Il settore residenziale.* Pubblicazioni OMI.

Osterman, P. (2020). *Creating Good Jobs. An Industry-Based Strategy*. The MIT Press.

Owen, G. (1977). Values of Games with a Priori Unions. *Mathematical Economics and Game Theory*. doi:10.1007/978-3-642-45494-3_7

Raitano, M., Jessoula, M., Gallo, G., & Pagnini, C. (2021). *Fighting poverty and social exclusion-including through minimum income schemes*. European Parliament.

Riphahn, R. T. (2001). Rational poverty or poor rationality? The take-up of social assistance benefits. *Review of income and wealth*, *47* (3), 379–398sa

Riphahn, R. T., & Wunder, C. (2013). Patterns of welfare dependence before and after a reform: Evidence from first generation immigrants and natives in Germany. *Review of Income and Wealth*, *59*(3): 437-459.

Salvati, L., Zitti, M., & Carlucci, M. (2016). In-between regional disparities and spatial heterogeneity: a multivariate analysis of territorial divides in Italy. *Journal of Environmental Planning and Management*, *60*(6), 997–1015. https://doi.org/10.1080/09640568.2016.1192023

Saraceno, C. (2016). Varieties of familialism: Comparing four southern European and East Asian welfare regimes. *Journal of European Social Policy*, *26*(4): 314-326.

Saraceno, C. (2021). *Il Welfare. Tra vecchie e nuove disuguaglianze*. Bologna: Il Mulino.

Saraceno, C., Benassi, D., & Morlicchio, E. (2022). I regimi di povertà in Europa e il caso Italiano. In C. Saraceno, D. Benassi & E. Morlicchio (eds.), *La povertà in Italia*. Bologna: Il Mulino.

Shapley, L. S. (1953). A Value for n-person Games. *Contributions to the Theory of Game*. doi:http://dx.doi.org/10.1017/CBO9780511528446.003

Spano P, Trivellato U, Zanini N (2013) Le esperienze italiane di misure di contrasto della povertà: che cosa possiamo imparare? *Economia e Società Regionale 31*(2):141–180.

Van Oorschot, W. (1991). Non-take-up of social security benefits in Europe. *Journal of European social policy*, *1* (1), 15–30.

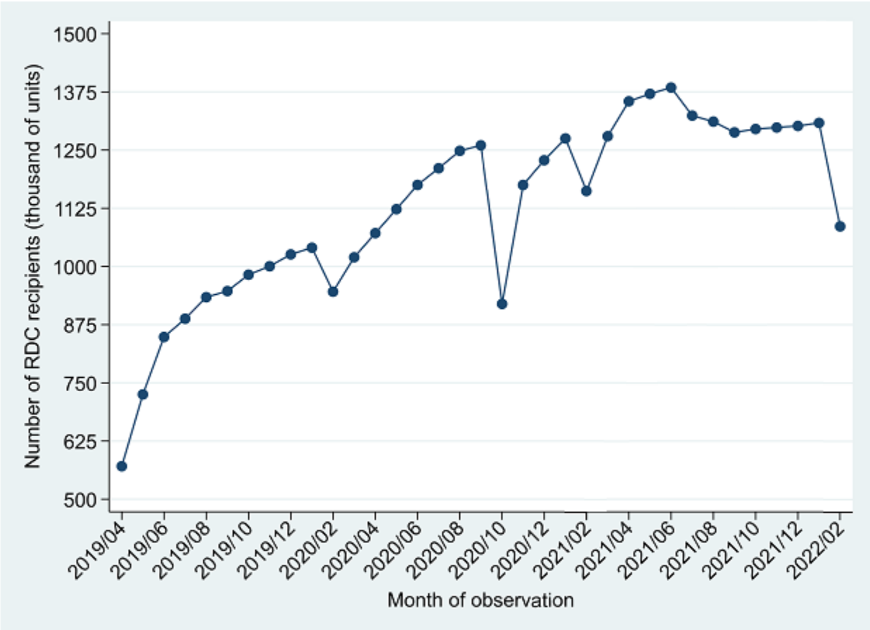
Van Oorschot,W. (1996) Modelling non-take-up: the interactive model of multi-level influences and the dynamic model of benefit receipt. In: Oorschot W, V (eds) New Perspectives on the non-Take-up of Social Security Benefits. Tilburg: Tilburg University Press, 7–59.

Van Oorschot, W. (2002). Targeting welfare: On the functions and dysfunctions of means-testing in social policy. In Townsend, P., & Gordon, D. (eds.), *World poverty: New policies to defeat an old enemy* (pp. 171-193). Policy Press.

Van Oorschot, W., & Roosma, F. (2015). The social legitimacy of differently targeted benefits. *Improve Discussion paper n°15/11*.

Vinck, J., Lebeer, J., & Van Lancker, W. (2019). Non-take-up of the supplemental child benefit for children with a disability in Belgium: A mixed-method approach. *Social Policy & Administration, 53*(3), 357-384.

Figure 1. Number of recipient households and share of new entrants of the Italian Minimum Income Scheme, from April 2019 to February 2022

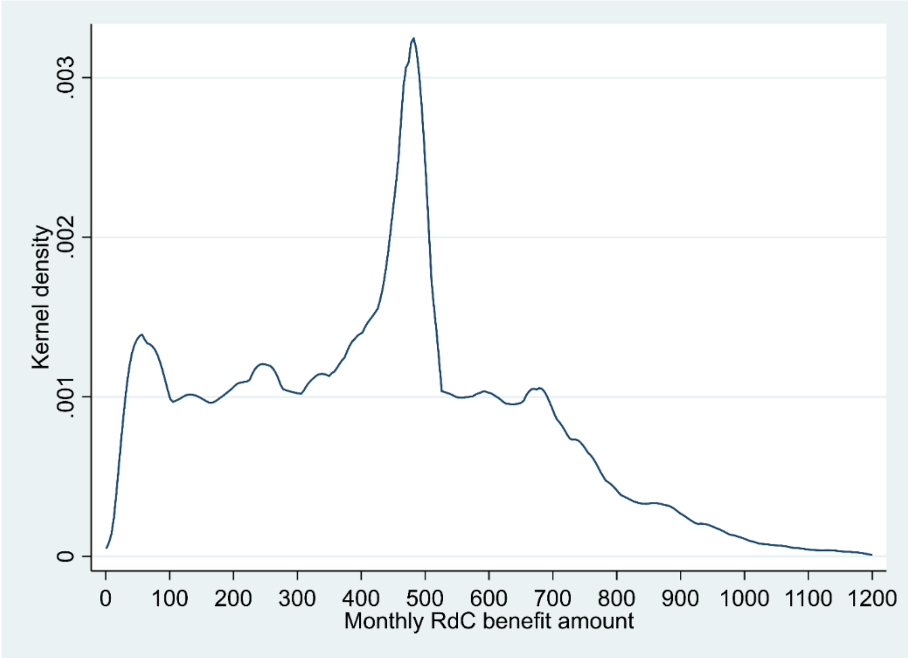


Source: authors elaboration on INPS administrative data.

Table 1. Summary of the main eligibility criteria and generosity of the Italian Minimum Income Scheme for a single person

Main eligibility criteria for a single person in 2021
Income and asset testing: • Income below 9,360 euros for those in a rented accommodation, and 6,000 euros if not renting. • Savings below 6,000 euros • Ownership of property of a value below 30,000 euros, excluding the first house • ISEE (Indicator of family economic condition) below 9,360 euros • Not having purchased a new car or motorbike recently and not owning boats **Residency and citizenship requirements:** • Residence in Italy for at least 10 years, of which the last two years were continuous • Being an EU citizen or a non-EU citizen with either a long-term resident permit or a resident permit for asylum seeker
Amount for a single person
• 500 euros per month, increased up 650 euros per month for those with a mortgage and 780 euros per month for those renting.

Figure 2. Distribution of the monthly amount of the Italian Minimum Income Scheme, from April 2019 to February 2022



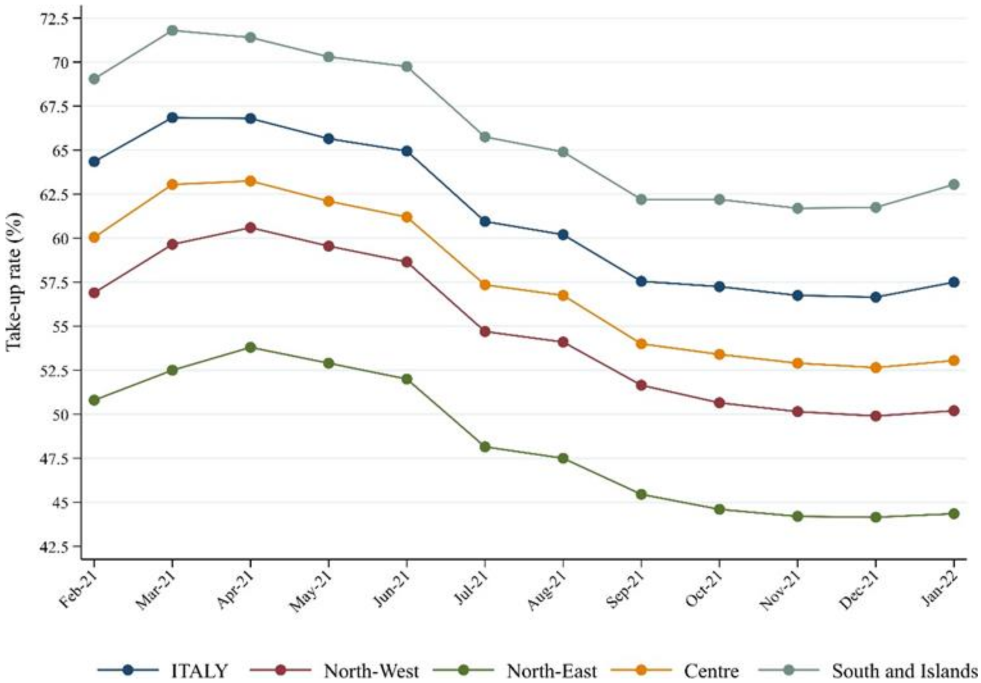
Source: authors' elaboration on INPS administrative data.

Table 2. Estimated eligible, recipient households and MIS take-up years 2019-2021

	2019	2020	2021
Estimates from Gallo and Raitano (2020)[a]			
Households eligible to MIS	1,751,063	1,776,856	
Households receiving MIS	1,073,294	1,304,259	
Estimated take-up of MIS	61.29%	73.40%	
Estimates based on INPS administrative data [b]			
Households eligible to MIS (average over 12 months)			2,077,895
Households receiving MIS (average over 12 months)			1,267,879
Estimated take-up of MIS (average over 12 months)			61.30%

Notes: [a] In Gallo and Raitano (2020) the potential number of households receiving the MIS is estimated using the 2017 AD-SILC sample data as sources, while the number of recipient households is obtained from INPS data. [b] The eligible pool of households is estimated on the universe of ISEE declarations below €9,360. Recipient households are estimated from the INPS archive on MIS. The number of eligible households, recipient households and the annual take-up of MIS are calculated as the arithmetic mean of monthly values estimated over 12 months.

Figure 3a. Monthly take-up rate trend by macro-area, February 2021- January 2022



Source: authors' elaboration on INPS administrative data.

Figure 3b. Take-up at the municipal level in March (left panel) and December (right panel) 2021.

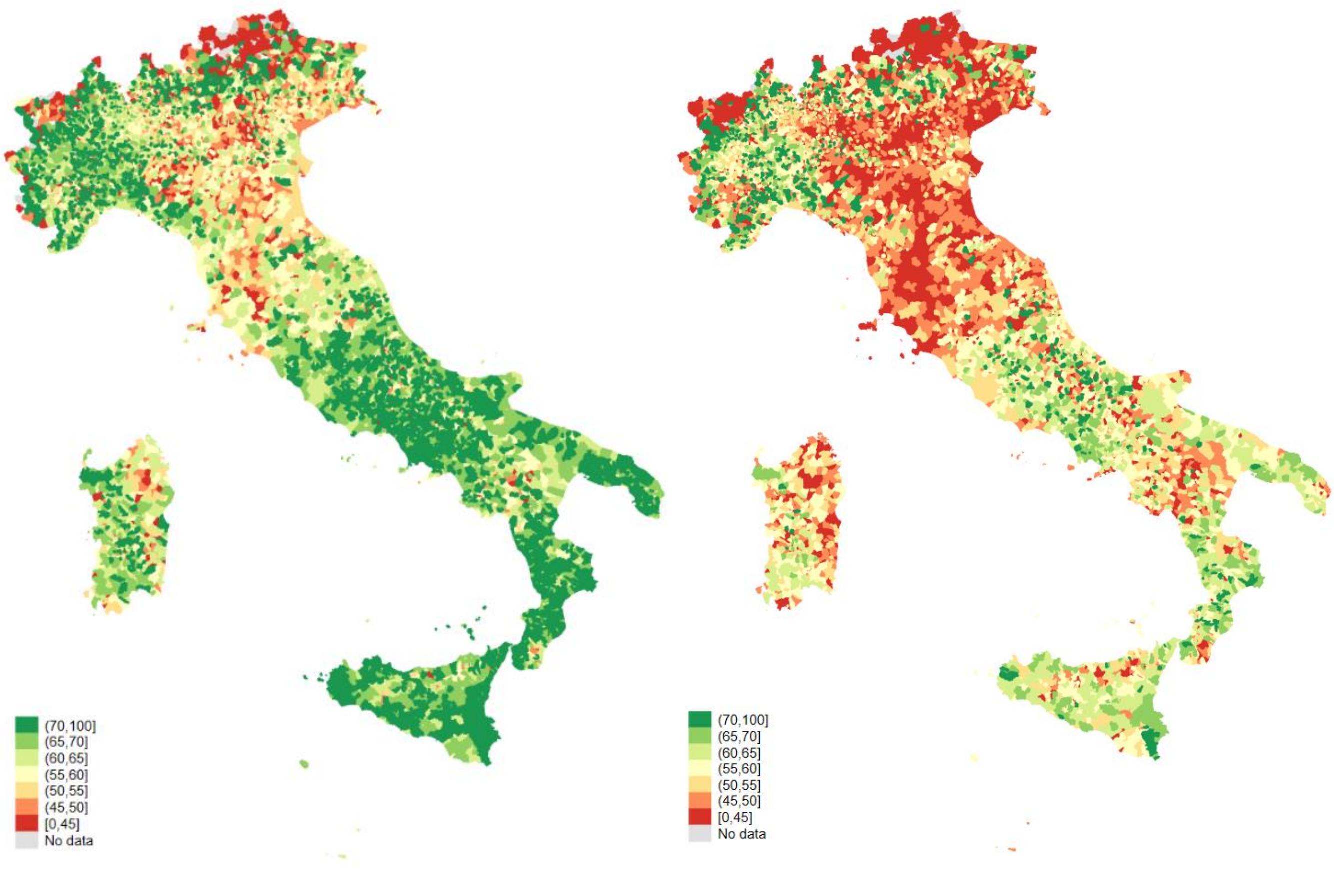
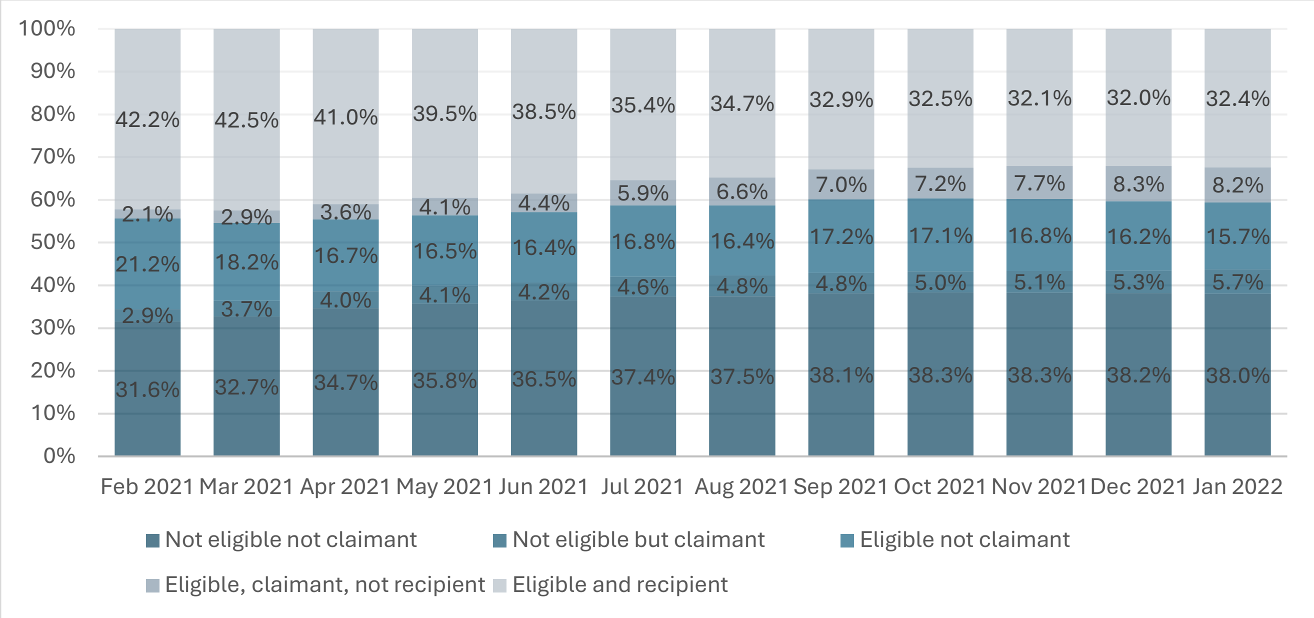
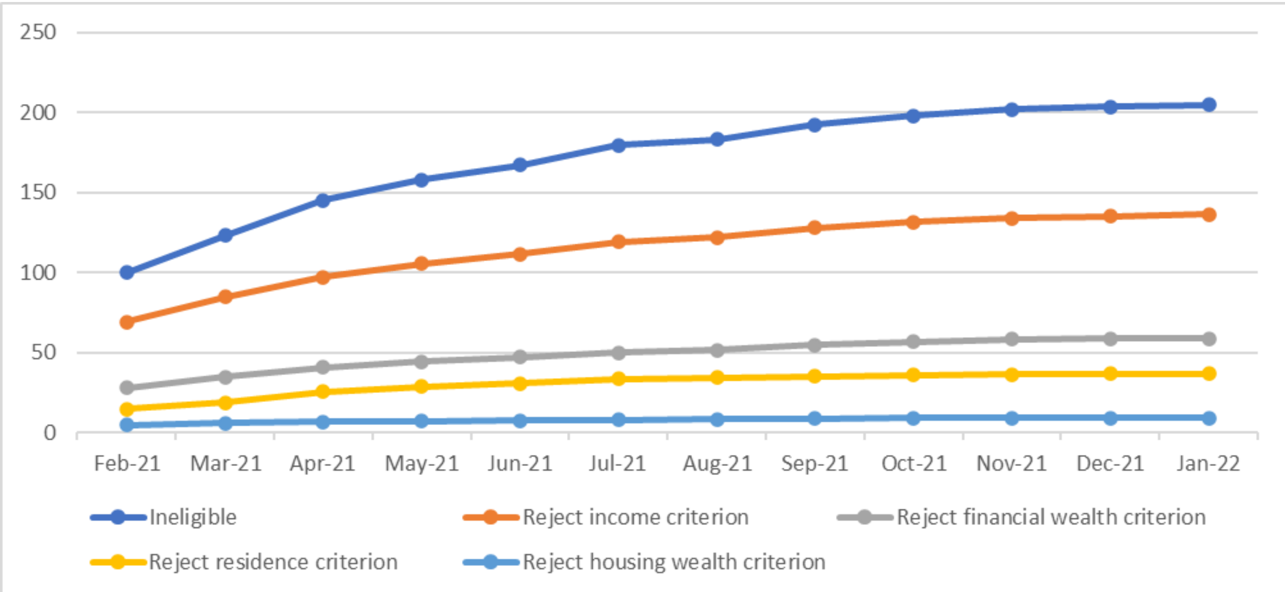


Figure 4. Monthly percentage of households by eligibility, claimant and recipient status on the total households with ISEE below 9,360 euros.



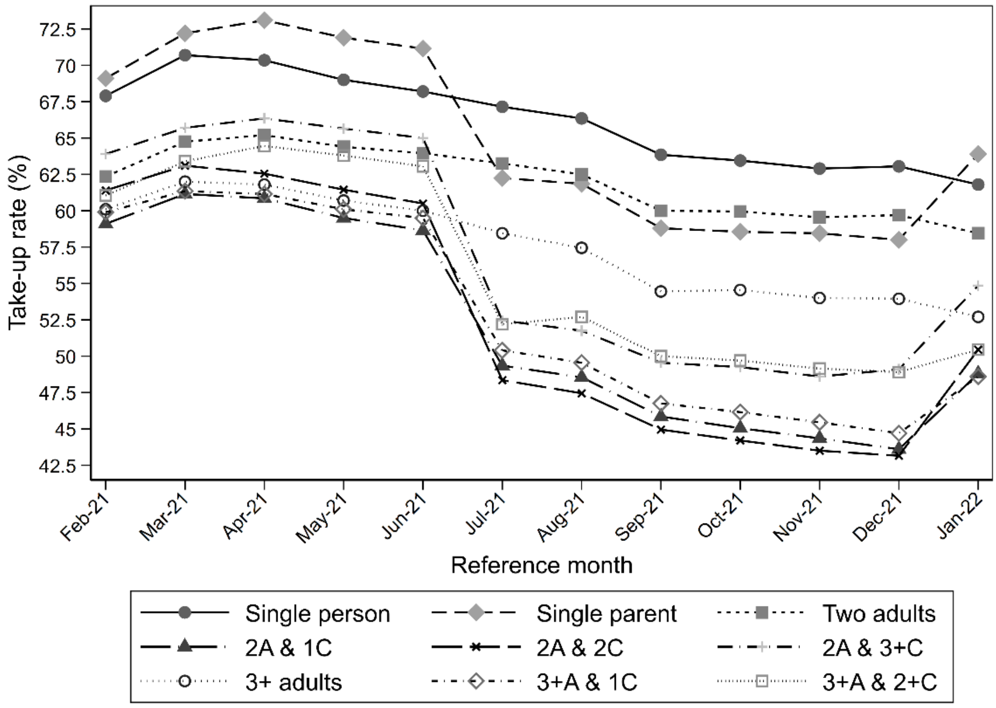
Source: elaboration on INPS administrative data.

Figure 5. Relative monthly trend of households with ISEE below 9,360 euros, ineligible to MIS, and by type of requirement violated (100=number of ineligible households with ISEE below 9,360 euros in February 2021)



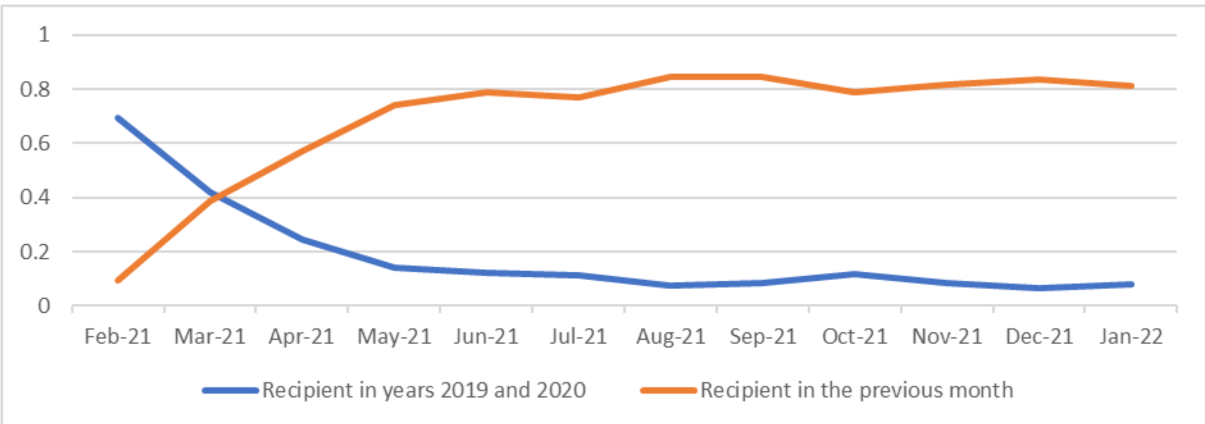
Note: The graph shows the values of the indicated variables as a percentage of the total number of households with ISEE below 9,360 euros as of February 2021 (about 2.5 million households). Source: elaboration on INPS administrative data.

Figure 6. Monthly take-up rate trend by household type, February 2021- January 2022



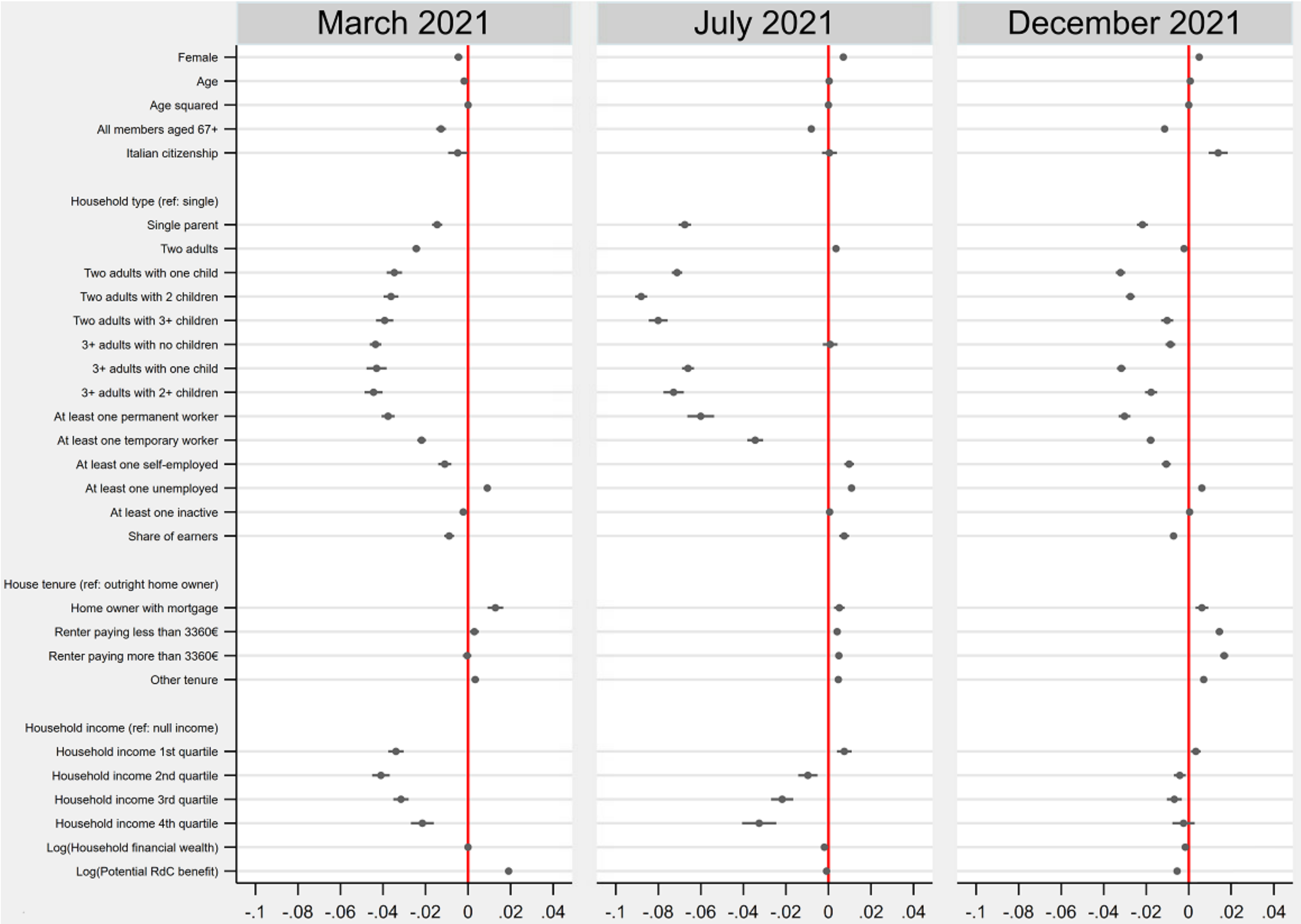
Note: A stands for "Adults" and C for "Child/Children". For example 2A&1C refers to an household with two adults and one child.
Source: elaboration on INPS administrative data.

Figure 7. Monthly coefficients from regression of MIS take up on receipt in previous years or in the previous month, February 2021-January 2022.



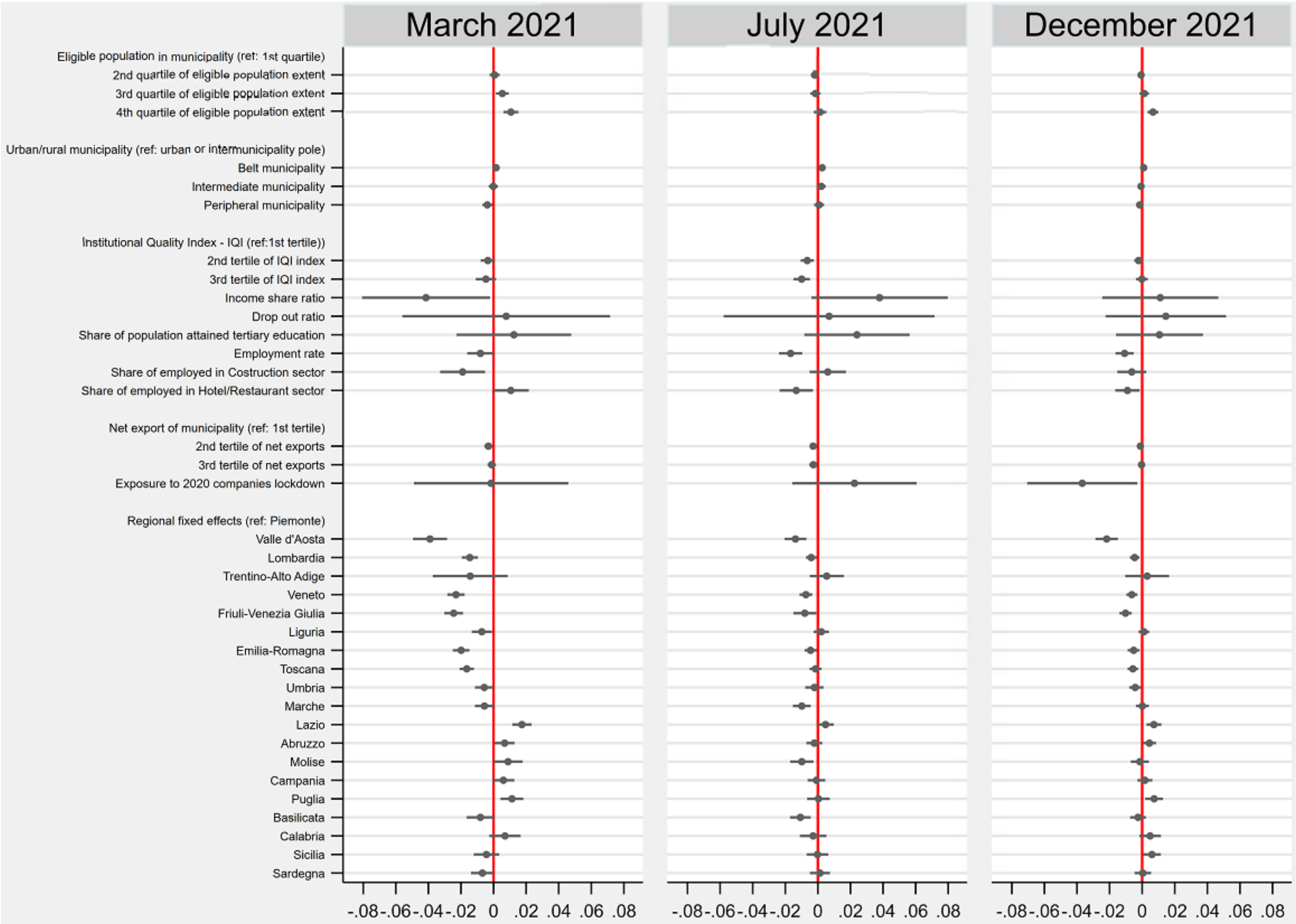
Note: The baseline linear probability regression is as per specification showed in Figure 8. The full table of coefficients for the other months is available upon request. Source: authors elaboration on INPS administrative data and provincial and municipal level data from external sources.

Figure 8. Linear probability model of take-up of Minimum Income Scheme on household and policy design variables.



Note: bars represent 95% confidence intervals. The number of observations amounts to 1,834,860 in March 2021, 2,116,532 in July 2021 and 2,260,311 in December 2021. The full model includes also a dummy indicating if the household received the MIS in 2019 or 2020, a dummy indicating if the household received MIS the month before, and the variables at the municipal, provincial and regional level related to the context. Coefficients for these variables are showed in Figure 9. The specification includes also a variable for the proportion of crimes and Covid-19 cases per 1000 inhabitants at the NUTs-3 level but the coefficients are omitted to keep the graph readable.

Figure 9. Linear probability model of take-up of Minimum Income Scheme on municipal, provincial and regional-level variables.



Note: bars represent 95% confidence intervals. The number of observations amounts to 1,834,860 in March 2021, 2,116,532 in July 2021 and 2,260,311 in December 2021. The full model includes also a dummy indicating if the household received the MIS in 2019 or 2020, a dummy indicating if the household received MIS the month before, and the variables at household and policy level. Coefficients for these variables are showed in Figure 8. The specification includes also a variable for the proportion of crimes and Covid-19 cases per 1000 inhabitants at the NUTs-3 level but the coefficients are omitted to keep the graph readable. For context variables sources and definitions see Table A2 of the appendix.

Table 3. Owen value decomposition of R-squared for the baseline models predicting take-up of Minimum Income Scheme.

Variable group	Group % R-squared		
	March 2021	July 2021	December 2021
Previous MIS use: in 2019 and 2020, in the previous month	88.28	88.09	88.81
Household head characteristics: Age, gender, nationality	1.07	1.13	1.42
Household characteristics: type, employment status of members	3.97	5.45	4.97
Policy design: dwelling type, income, wealth, MIS amount	4.52	3.78	3.26
Contextual variables at the municipal and provincial level	1.07	0.80	0.83
Regional fixed effects	1.09	0.73	0.72
Total	100.00	100.00	100.00

Notes: This table reports the fraction of the overall R-squared (per cent), explained by the different groups of characteristics – also known as Owen value. The values are calculated for March, July and December 2021 considering the specification showed in the baseline linear probability models in Figures 8 and 9.

Table 4. Multinomial logit model for the determinants of eligibility and recipient status (March 2021), log-odds.

	March 2021	
Y base category= non-eligible non-recipients	Y= eligible non-recipients	Y= eligible recipients
Benefit recipient in 2019 or 2020	0.27***	4.22***
Female	0.13***	0.07***
Age	0.09***	0.07***
Age squared	0.00***	0.00***
All household members above 67	0.51***	0.32***
Italian citizen	0.79***	0.85***
Household type (Ref: Single)		
Single parent	0.43***	0.38***
Two adults	0.69***	0.51***
Two adults with one child	1.10***	0.86***
Two adults with 2 children	1.37***	1.30***
Two adults with 3+ children	1.66***	1.81***
3+ adults with no children	1.49***	1.22***
3+ adults with one child	1.67***	1.43***
3+ adults with 2+ children	1.70***	1.64***
Permanent worker within household	0.13***	-0.33***
Temporary worker within household	0.16***	-0.19***
Self-employed within household	-0.08***	-0.27***
Unemployed within household	0.18***	0.27***
Inactive person within household	0.02	-0.02*
Share of earners within households	-0.12***	-0.26***
House tenure (ref: outright owner)		
Home owner with mortgage	-0.12***	0.06***
Renter paying less than 3360€	1.75***	1.85***
Renter paying more than 3360€	1.64***	1.76***
Other tenure	0.43***	0.38***
Household income (ref: null income)		
1st income quartile	0.37***	0.07
2nd income quartile	0.20***	-0.44***
3rd income quartile	-1.02***	-1.7***
4th income quartile	-3.45***	-4.1***
Logarithm of savings	-0.27***	-0.29***
Eligible population in municipality (ref: 1st quartile)		
2nd quartile eligible	0.01	0.03
3rd quartile eligible	0.04*	0.14***
4th quartile eligible	0.12***	0.31***
Urban/rural municipality (ref: urban or intermunicipal pole)		
Belt municipality	-0.01	0.00
Intermediate municipality	0.00	-0.01
Peripheral municipality	0.03*	-0.01
Institutional Quality Index - IQI (ref: 1st tertile)		
2nd tertile of IQI index	-0.01	-0.07**
3rd tertile of IQI index	0.01	-0.06
Income share ratio	0.23	-0.1
Dropout rate	-2.15***	-1.86***

Table continues in the next page

Proportion of crimes per 1000 inhabitants	-0.09	0.12
Share of population attained tertiary education	-0.84***	-0.67*
Employment rate	-0.16***	-0.26***
Share of employed in construction sector	-0.06	-0.16
Share of employed in hotel/restaurant sector	0.38***	0.32***
Net export of municipality (ref: 1st tertile)		
2nd tertile of net exports	0.02	-0.01
3rd tertile of net exports	0.05***	0.02
Covid-19 cases in 2020	-0.95	-0.96
Exposure to 2020 companies' lockdown	-0.18	-0.24
Regional level fixed-effect included	Yes	Yes
Observations	2,887,016	2,887,016

*Notes: Standard errors are clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1. For context level variables sources and definitions see Table A2 of the appendix.*

Appendix

Table A1. Household descriptive statistics for the months of March, July and December 2021.

Characteristic	All households with ISEE<9,360			Eligible households			Claimant households			Recipient households		
	Mar 2021	Jul 2021	Dec 2021	Mar 2021	Jul 2021	Dec 2021	Mar 2021	Jul 2021	Dec 2021	Mar 2021	Jul 2021	Dec 2021
Household head: female	0.532	0.522	0.523	0.548	0.546	0.546	0.546	0.546	0.547	0.546	0.545	0.551
Household head age	49.5	48.8	48.5	50.6	50.3	50.0	50.2	50.0	49.7	50.5	50.9	50.9
Household head: Italian citizen	0.723	0.701	0.706	0.780	0.770	0.772	0.800	0.785	0.781	0.811	0.813	0.823
Equivalised scale	1.911	1.891	1.891	1.781	1.758	1.751	1.774	1.765	1.758	1.753	1.694	1.683
Single person	0.360	0.370	0.369	0.414	0.424	0.427	0.421	0.426	0.430	0.438	0.467	0.475
Single parent	0.062	0.063	0.064	0.067	0.067	0.069	0.071	0.072	0.075	0.072	0.069	0.070
Two adults	0.141	0.134	0.132	0.153	0.151	0.149	0.151	0.151	0.149	0.148	0.157	0.157
Two adults with one child	0.094	0.095	0.096	0.080	0.080	0.080	0.077	0.077	0.076	0.073	0.065	0.062
Two adults with 2 children	0.095	0.098	0.100	0.070	0.069	0.069	0.069	0.068	0.069	0.066	0.054	0.053
Two adults with 3+ children	0.050	0.047	0.047	0.033	0.031	0.032	0.034	0.034	0.035	0.033	0.027	0.027
3+ adults with no children	0.101	0.099	0.099	0.104	0.102	0.100	0.099	0.096	0.092	0.097	0.098	0.095
3+ adults with one child	0.056	0.055	0.055	0.049	0.047	0.046	0.047	0.045	0.043	0.045	0.039	0.036
3+ adults with 2+ children	0.042	0.040	0.039	0.030	0.028	0.028	0.031	0.031	0.030	0.029	0.024	0.024
Permanent worker within household	0.218	0.237	0.242	0.125	0.134	0.137	0.102	0.113	0.117	0.085	0.073	0.069
Temporary worker within household	0.109	0.119	0.120	0.082	0.088	0.089	0.072	0.076	0.077	0.064	0.059	0.057
Self-employed within household	0.054	0.063	0.070	0.043	0.049	0.052	0.037	0.039	0.039	0.035	0.036	0.036
Unemployed within household	0.534	0.505	0.493	0.611	0.594	0.584	0.649	0.638	0.632	0.658	0.656	0.653
Inactive person within household	0.396	0.398	0.402	0.366	0.366	0.368	0.360	0.358	0.358	0.354	0.343	0.342
Share of earners in household	0.285	0.300	0.305	0.242	0.253	0.256	0.210	0.218	0.219	0.202	0.207	0.207
Underage children within household	0.398	0.396	0.395	0.328	0.321	0.318	0.327	0.325	0.323	0.317	0.277	0.270
Household with people aged 67+ only	0.176	0.165	0.163	0.178	0.173	0.171	0.158	0.158	0.155	0.159	0.165	0.166
Outright home owner	0.142	0.138	0.136	0.125	0.120	0.116	0.126	0.118	0.112	0.123	0.119	0.114
Home owner with mortgage	0.037	0.040	0.039	0.017	0.017	0.016	0.018	0.019	0.018	0.015	0.014	0.013
Renter paying less than 3360€	0.162	0.150	0.146	0.193	0.187	0.184	0.186	0.183	0.181	0.195	0.194	0.195
Renter paying more than 3360€	0.254	0.250	0.250	0.237	0.239	0.241	0.229	0.237	0.241	0.224	0.221	0.222
Other tenure	0.405	0.422	0.429	0.429	0.437	0.443	0.441	0.442	0.449	0.443	0.453	0.457

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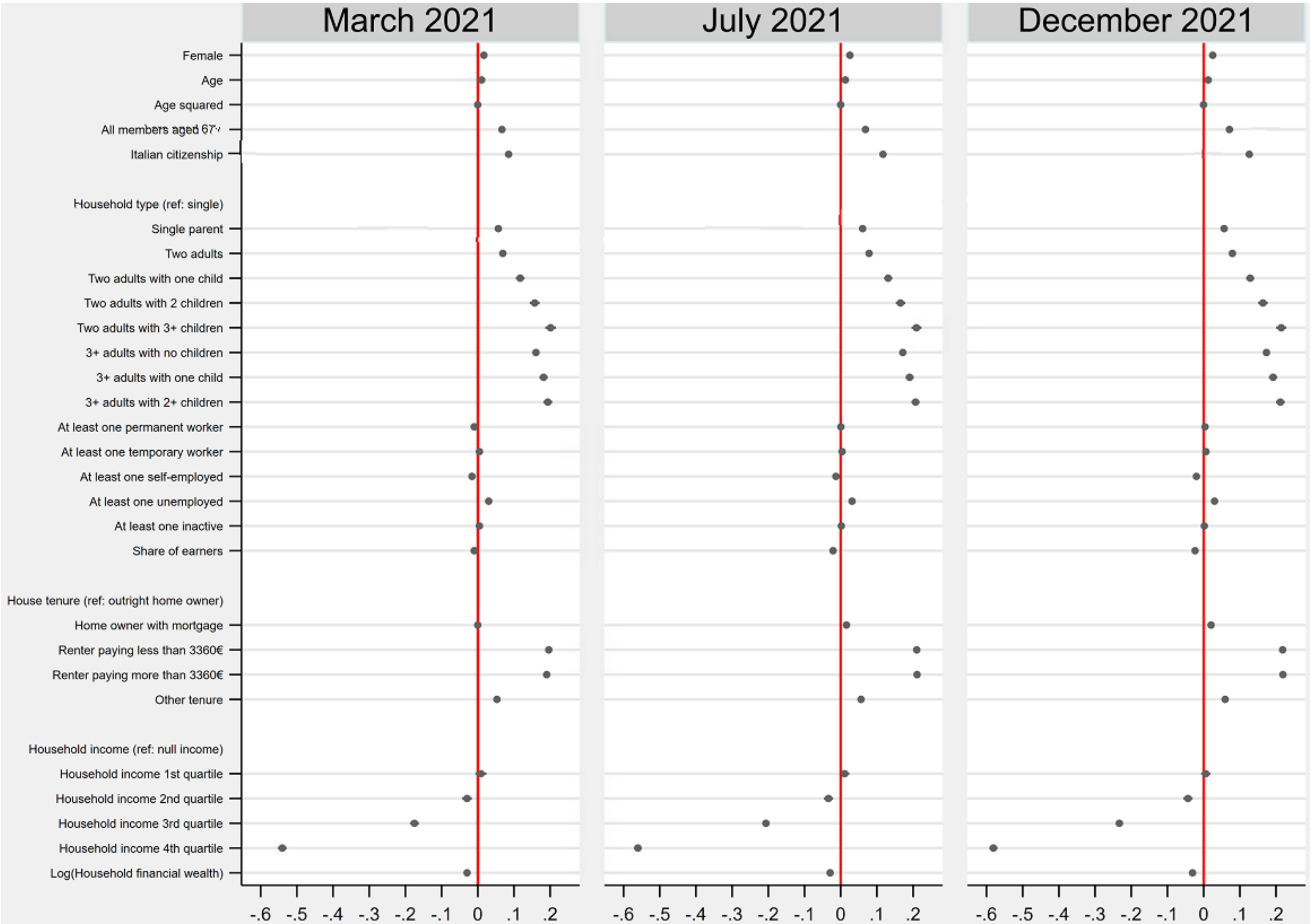
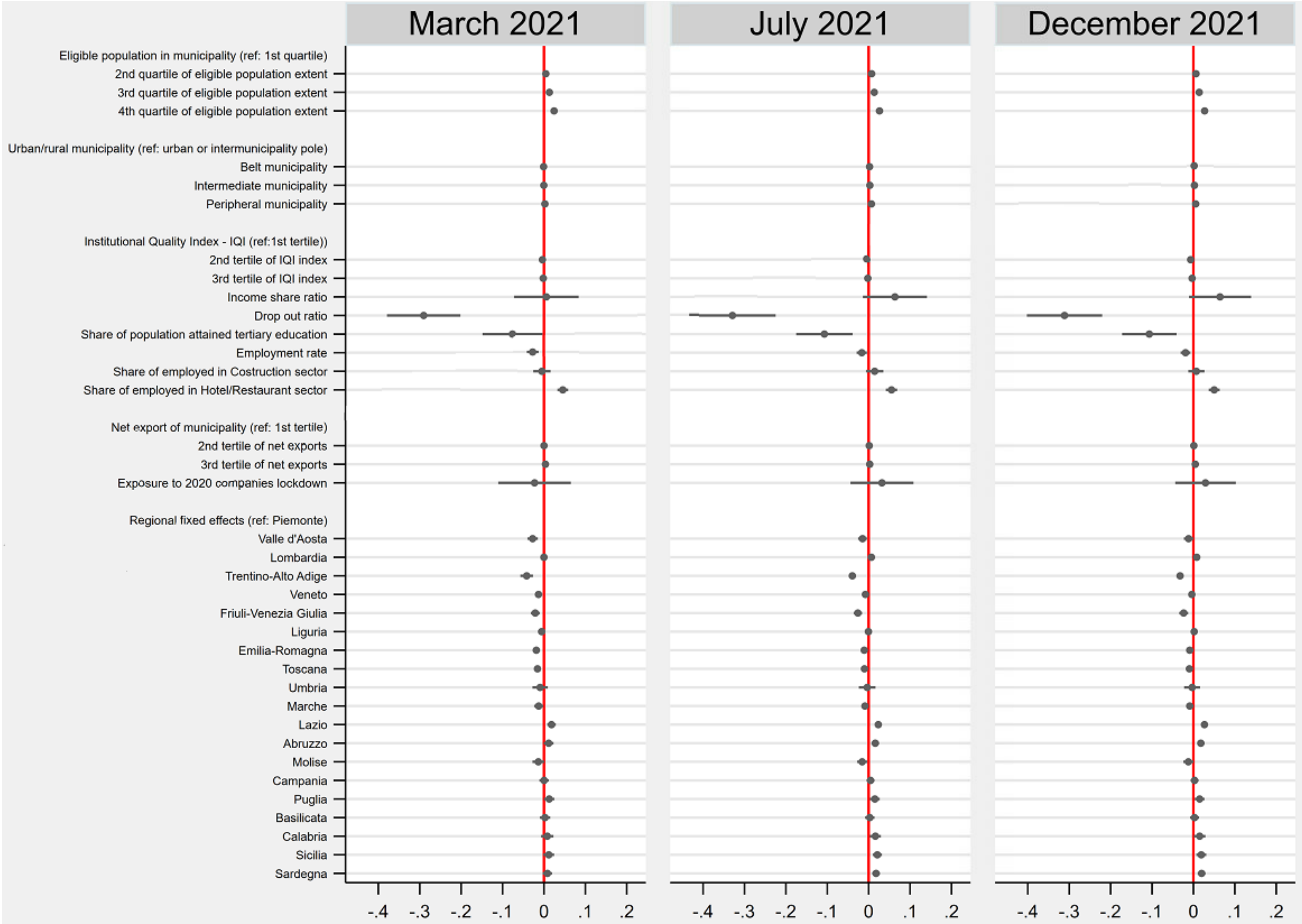
Income value = 0	0.109	0.120	0.124	0.131	0.144	0.153	0.123	0.131	0.142	0.132	0.146	0.152
Income quintile group = 1	0.178	0.176	0.175	0.228	0.231	0.233	0.229	0.231	0.232	0.241	0.253	0.259
Income quintile group = 2	0.178	0.176	0.175	0.242	0.247	0.248	0.250	0.249	0.246	0.264	0.276	0.280
Income quintile group = 3	0.178	0.176	0.175	0.208	0.208	0.206	0.201	0.199	0.196	0.200	0.200	0.198
Income quintile group = 4	0.178	0.176	0.175	0.150	0.138	0.131	0.144	0.135	0.129	0.131	0.105	0.095
Income quintile group = 5	0.178	0.176	0.175	0.041	0.032	0.029	0.054	0.055	0.056	0.032	0.020	0.017
Log(Financial wealth)	5.926	5.999	6.049	5.130	5.160	5.156	5.040	5.096	5.094	4.826	4.773	4.738
Potential MIS monthly benefit (€)	278.3	246.0	237.7	437.9	424.1	420.4	433.1	404.6	393.0	477.8	464.8	458.6
Share of MIS recipients in 2019 or 2020	0.404	0.342	0.317	0.605	0.554	0.524	0.824	0.745	0.695	0.854	0.790	0.750
Share of MIS eligible	0.636	0.580	0.565	0.714	0.711	0.713	0.924	0.899	0.884			
Share of MIS claimants	0.491	0.459	0.456									
Total households	2,887,016	3,648,396	3,997,423	1,834,860	2,116,532	2,260,311	1,417,863	1,673,736	1,822,075	1,226,363	1,290,104	1,280,985

Figure A1(a). *Linear probability model of eligibility to Minimum Income Scheme on household and policy design variables (universe of households with ISEE below 9360).*



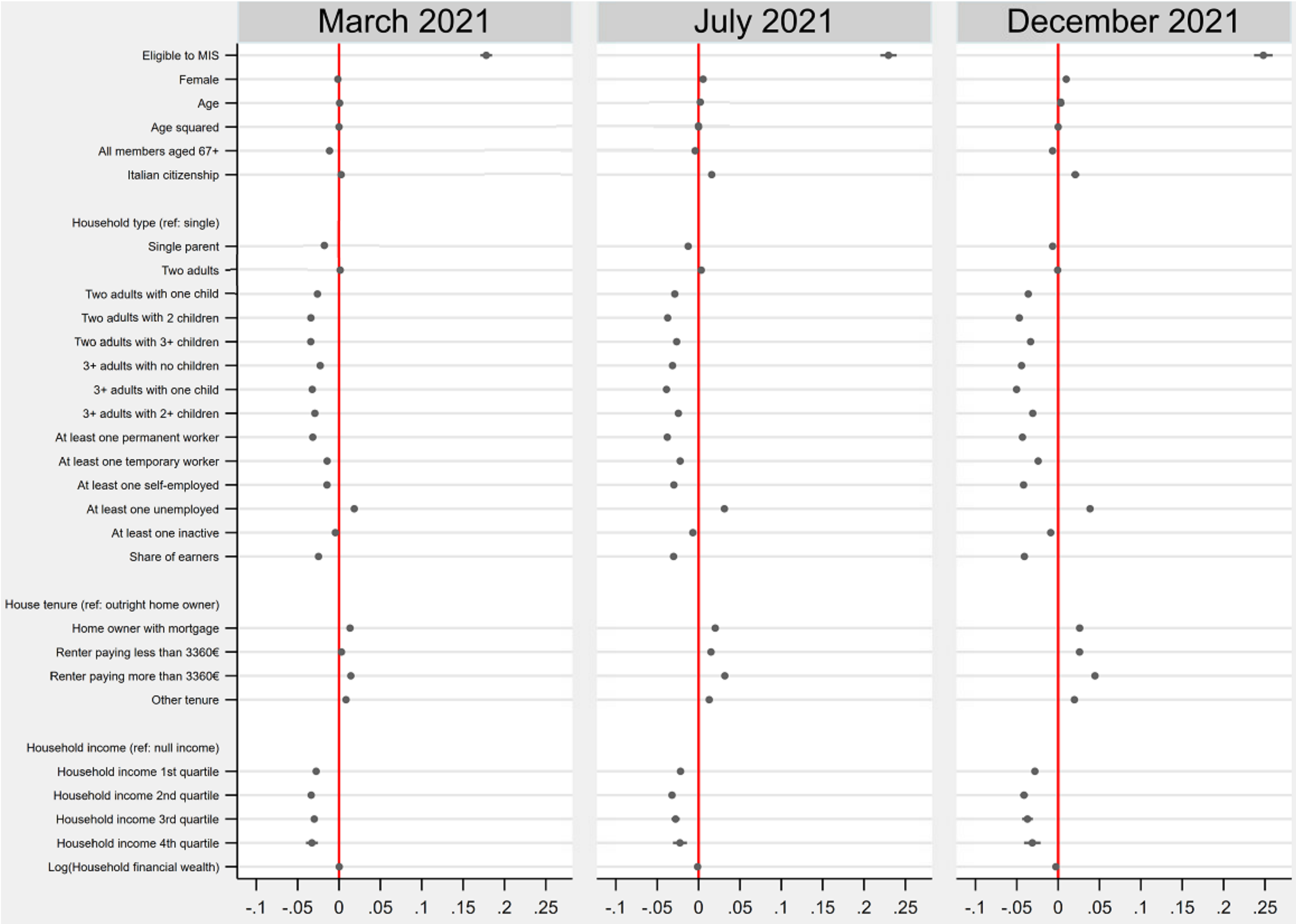
Note: bars represent 95% confidence intervals. The full model includes also a dummy indicating if the household received the MIS in 2019 or 2020, a dummy indicating if the household received MIS the month before, and the variables at the municipal, provincial and regional level related to the context. Coefficients for these variables are showed in Figure A1(b). The specification includes also a variable for the proportion of crimes and Covid-19 cases per 1000 inhabitants at the NUTs-3 level but the coefficients are omitted to keep the graph readable.

Figure A1(b). Linear probability model of eligibility to Minimum Income Scheme on municipal, provincial and regional -level variables (universe of households with ISEE below 9360).



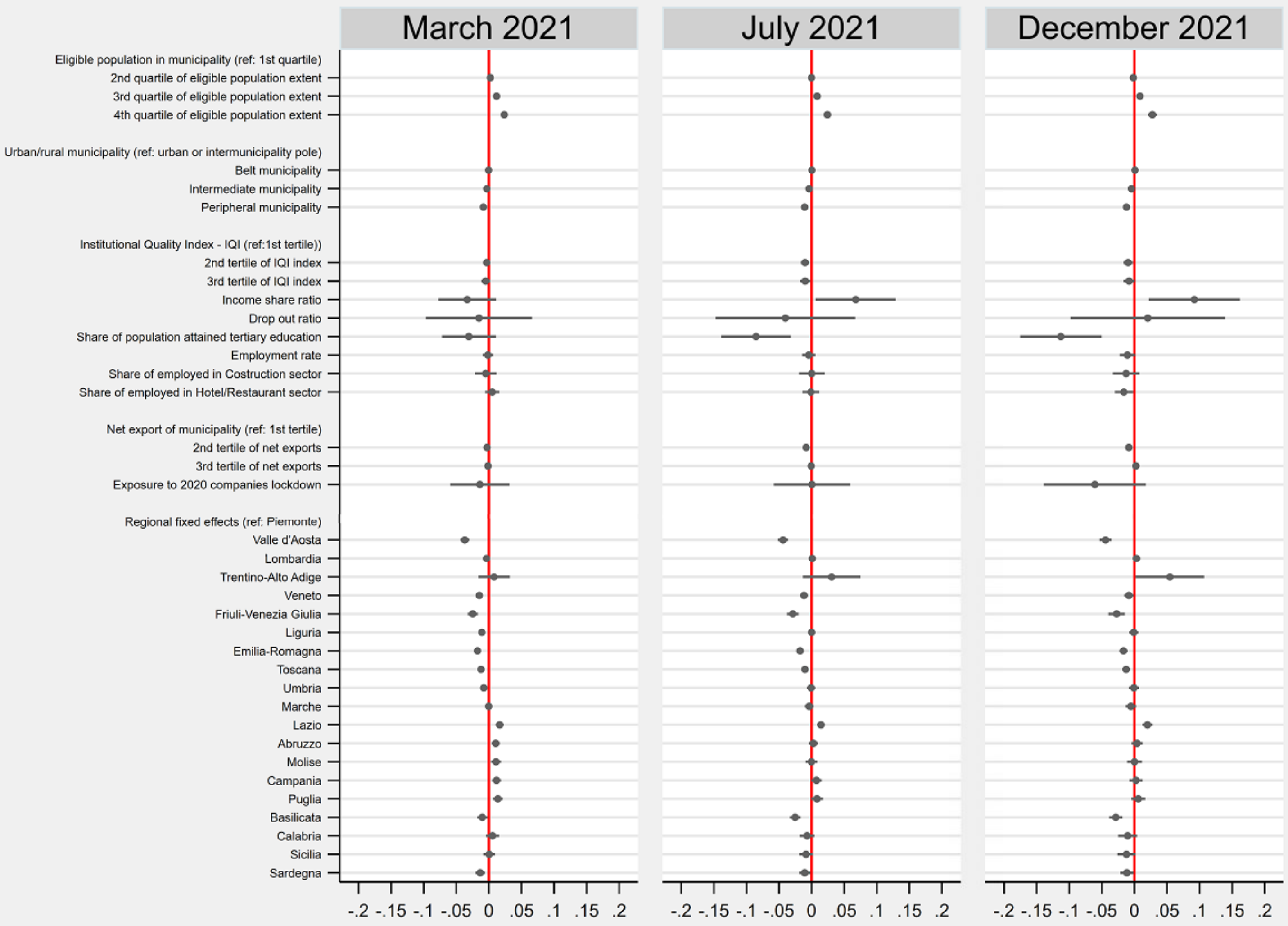
Note: bars represent 95% confidence intervals. The full model includes also a dummy indicating if the household received the MIS in 2019 or 2020, a dummy indicating if the household received MIS the month before, and the variables at household and policy level. Coefficients for these variables are showed in Figure A1(a). The specification includes also a variable for the proportion of crimes and Covid-19 cases per 1000 inhabitants at the NUTs-3 level but the coefficients are omitted to keep the graph readable. For variables sources and definitions see Table A2 of the appendix.

Figure A2(a). Linear probability model of application to Minimum Income Scheme on *household and policy design variables (universe of households with ISEE below 9360).*



Note: bars represent 95% confidence intervals. The full model includes also a dummy indicating if the household received the MIS in 2019 or 2020, a dummy indicating if the household received MIS the month before, and the variables at the municipal, provincial and regional level related to the context. Coefficients for these variables are showed in Figure A2(b). The specification includes also a variable for the proportion of crimes and Covid-19 cases per 1000 inhabitants at the NUTs-3 level but the coefficients are omitted to keep the graph readable.

Figure A2(b). Linear probability model of application to Minimum Income Scheme on municipal, provincial and regional -level variables (universe of households with ISEE below 9360).



Note: bars represent 95% confidence intervals. The full model includes also a dummy indicating if the household received the MIS in 2019 or 2020, a dummy indicating if the household received MIS the month before, and the variables at household and policy level. Coefficients for these variables are showed in Figure A2(a). The specification includes also a variable for the proportion of crimes and Covid-19 cases per 1000 inhabitants at the NUTs-3 level but the coefficients are omitted to keep the graph readable. For variables sources and definitions see Table A2 of the appendix.

Table A2. Definition and sources of the aggregate level variables.

Aggregate level variables from external sources	Source
Quartiles of population eligible to MIS, by municipality	Authors' calculations on INPS/ISTAT
Urban/rural municipality	Ministry of Economic Development (2014)
Institutional Quality Index at the province level.	Ninfo and Vecchione (2014)
Income share ratio	Ministry of Economics and Finance (2019)
Drop out ratio	ISTAT (2011)
Share of population that attained tertiary education	ISTAT (2011)
Employment rate	ISTAT (2019)
Proportion of employed in construction	ISTAT (2019)
Proportion of employed in hotel/restaurant sector	ISTAT (2019)
Net export in NUTS-3 level	Coeweb ISTAT (2016)
Exposure to 2020 companies' lockdown	Bonacini, Gallo & Patriarca (2021)
Covid-19 cases every 1000 inhabitants at the NUTS-3 level	Italian Civil Protection Department (2020)
Proportion of crimes per 1000 inhabitants at NUTS-3 level	Ministry of Interior (2018)

Note: The Income share ratio is defined as the total amount of income reported by taxpayers declaring €55,000 or more divided by total amount of income reported by taxpayers declaring €10,000 or lower in the municipality. The dropout rate is defined as the share of people aged 15-62 who dropped out from primary school. The exposure to 2020 companies lockdown is calculated as the proportion of workers in sectors affected by the 2020 lockdown.

Table A3. Linear probability model predicting MIS receipt in the months of March 2021 (1), July 2021 (2) and December 2021 (3), for single-person households only.

VARIABLES	(1) March 2021	(2) July 2021	(3) December 2021
Benefit recipient in February 2021	0.329***		
Benefit recipient in June 2021		0.833***	
Benefit recipient in November 2021			0.835***
Benefit recipient in 2019 or 2020	0.432***	0.075***	0.030***
Female	-0.005***	0.005***	0.007***
Age	-0.004***	-0.000	0.001***
Age squared	0.000***	0.000	-0.000***
All household members above 67	0.005***	-0.001	-0.000
Italian citizen	-0.032***	0.013***	0.017***
Permanent worker within household	-0.029***	-0.011***	-0.018***
Temporary worker within household	-0.007***	-0.011***	-0.013***
Self-employed within household	0.021***	-0.006***	-0.004
Unemployed within household	-0.010**	0.006	-0.072***
Inactive person within household	-0.020***	0.002	-0.080***
Share of earners within households	-0.033***	0.000	-0.084***
House tenure (ref: outright owner)			
Home owner with mortgage	-0.005	-0.003*	-0.013***
Renter paying less than 3360€	-0.020***	-0.002	-0.000
Renter paying more than 3360€	-0.035***	-0.004***	-0.011***
Other tenure	-0.004***	0.002***	0.003***
Household income (ref: null income)			
1st income quartile	-0.022***	0.021***	0.013***
2nd income quartile	-0.016***	0.013***	0.032***
3rd income quartile	-0.002	0.024***	0.052***
4th income quartile	0.086***	0.058***	0.104***
Logarithm of savings	0.000	-0.001***	-0.001***
Log(potential MIS amount)	0.070***	0.030***	0.044***
Eligible population in municipality (ref: 1st quartile)			
2nd quartile eligible	-0.001	-0.001	-0.002
3rd quartile eligible	0.005**	-0.003	-0.005***
4th quartile eligible	0.005	-0.000	0.001
Urban/rural municipality (ref: urban or intermunicipal pole)			
Belt municipality	0.001	0.002	-0.001
Intermediate municipality	0.003	-0.000	-0.002
Peripheral municipality	-0.002	-0.000	-0.001
Institutional Quality Index - IQI (ref: 1st tertile)			
2nd tertile of IQI index	-0.001	0.004*	0.002
3rd tertile of IQI index	-0.004	0.002	0.003
Inequality index	-0.021	0.043**	0.012
Dropout rate	-0.021	0.085***	0.039
Proportion of crimes per 1000 inhabitants	-0.038	0.079	0.068
Proportion with university degree	-0.038	-0.015	0.000
Employment rate	-0.006	-0.007	-0.010***
Share of employed in construction sector	-0.034***	-0.008	-0.012*
Share of employed in hotel/restaurant sector	0.030***	-0.003	0.001

Table continues in the next page

Net export of municipality (ref: 1st tertile)			
Medium export level	-0.003	-0.001	-0.002**
High export level	-0.002	0.002	0.003*
Covid-19 cases in 2020	0.142	0.094	0.040
Exposure to 2020 companies' lockdown	0.010	-0.071***	-0.053**
Regional fixed effects included	Yes	Yes	Yes
Observations	759,322	897,856	966,277
R-squared	0.611	0.823	0.783

*Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. For context level variables sources and definitions see Table A2 of the appendix.*

Table A4. Linear probability model predicting MIS receipt in the months of March 2021 (1), July 2021 (2) and December 2021 (3), for households in Northen Italy.

	(1) March 2021	(2) July 2021	(3) December 2021
Benefit recipient in 2019 or 2020	0.484***	0.085***	0.048***
Benefit recipient in February 2021	0.365***		
Benefit recipient in June 2021		0.792***	
Benefit recipient in November 2021			0.864***
Female	-0.004***	0.005***	0.002*
Age	-0.002***	0.001***	0.001***
Age squared	0.000***	-0.000***	-0.000***
All household members above 67	-0.003	-0.003***	-0.004***
Italian citizen	-0.003	0.007***	0.010***
Household type (Ref: Single)			
Single parent	-0.011***	-0.064***	-0.016***
Two adults	-0.023***	0.001	-0.005***
Two adults with one child	-0.041***	-0.065***	-0.029***
Two adults with 2 children	-0.040***	-0.089***	-0.024***
Two adults with 3+ children	-0.041***	-0.106***	-0.010***
3+ adults with no children	-0.048***	-0.009***	-0.016***
3+ adults with one child	-0.061***	-0.067***	-0.036***
3+ adults with 2+ children	-0.054***	-0.089***	-0.022***
Permanent worker within household	-0.038***	-0.042***	-0.021***
Temporary worker within household	-0.022***	-0.031***	-0.013***
Self-employed within household	-0.004	0.015***	-0.007***
Unemployed within household	0.013***	0.012***	0.007***
Inactive person within household	-0.003	0.001	0.001
Share of earners within household	-0.009***	0.006***	-0.005***
House tenure (ref: outright owner)			
Home owner with mortgage	0.009***	0.007***	0.001
Renter paying less than 3360€	-0.002	-0.003*	0.006***
Renter paying more than 3360€	-0.004**	0.003**	0.006***
Other tenure	0.003	0.001	0.002
Household income (ref: null income)			
1st income quartile	-0.028***	0.019***	0.010***
2nd income quartile	-0.028***	0.007	0.008***
3rd income quartile	-0.024***	-0.010**	0.008**
4th income quartile	0.037***	0.031***	0.046***
Logarithm of savings	-0.001*	-0.001***	-0.001***
Log(potential MIS amount)	0.022***	0.006***	0.001
Eligible population in municipality (ref: 1st quartile)			
2nd quartile eligible	0.003*	0.002	0.002
3rd quartile eligible	0.004*	0.003**	0.002
4th quartile eligible	0.005*	0.004**	0.001
Urban/rural municipality (ref: urban or intermunicipal pole)			
Belt municipality	-0.001	0.002	0.001
Intermediate municipality	0.001	0.001	-0.002
Peripheral municipality	0.003	-0.002	0.003
Institutional Quality Index - IQI (ref: 1st tertile)			
2nd tertile of IQI index	-0.002	-0.003**	-0.001
3rd tertile of IQI index	0.003	-0.001	0.001
Income share ratio	-0.027	0.035*	-0.050**
Dropout rate	0.148	-0.173**	-0.148**
Proportion of crimes per 1000 inhabitants	0.227**	-0.002	-0.059

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Share of population attained tertiary education	-0.020	-0.017	0.023
Employment rate	-0.010*	-0.008**	-0.005*
Share of employed in construction sector	-0.021	0.015*	-0.002
Share of employed in hotel/restaurant sector	0.007	-0.009	-0.015**
Net export of municipality (ref: 1st tertile)			
Medium export level	0.006***	0.003**	-0.001
High export level	0.002	0.004**	0.001
Covid-19 cases in 2020	0.242**	0.073	0.102
Exposure to 2020 companies' lockdown	0.024	-0.026	-0.030
Regional level fixed-effect included	Yes	Yes	Yes
Observations	451,290	540,192	581,432
R-squared	0.666	0.773	0.824

Notes: as per table A3.

Table A5. Linear probability model predicting MIS receipt in the months of March 2021 (1), July 2021 (2) and December 2021 (3), for households in Central Italy.

	(1) March 2021	(2) July 2021	(3) December 2021
Benefit recipient in 2019 or 2020	0.437***	0.093***	0.050***
Benefit recipient in February 2021	0.375***		
Benefit recipient in June 2021		0.793***	
Benefit recipient in November 2021			0.844***
Female	-0.012***	0.003***	0.001
Age	-0.001***	0.000**	0.001***
Age squared	0.000*	-0.000***	-0.000***
All household members above 67	-0.009***	-0.005***	-0.009***
Italian citizen	-0.012***	-0.005*	0.004
Household type (Ref: Single)			
Single parent	-0.016***	-0.074***	-0.019***
Two adults	-0.022***	0.003**	-0.005***
Two adults with one child	-0.054***	-0.071***	-0.038***
Two adults with 2 children	-0.047***	-0.091***	-0.032***
Two adults with 3+ children	-0.043***	-0.092***	-0.012***
3+ adults with no children	-0.046***	-0.000	-0.013***
3+ adults with one child	-0.056***	-0.060***	-0.037***
3+ adults with 2+ children	-0.054***	-0.079***	-0.030***
Permanent worker within household	-0.043***	-0.042***	-0.029***
Temporary worker within household	-0.027***	-0.028***	-0.019***
Self-employed within household	-0.003	0.015***	-0.006**
Unemployed within household	0.011***	0.007***	0.007***
Inactive person within household	-0.002	-0.004***	0.000
Share of earners within household	-0.011***	0.000	-0.008***
House tenure (ref: outright owner)			
Home owner with mortgage	0.006	0.006	-0.001
Renter paying less than 3360€	0.005**	0.002	0.010***
Renter paying more than 3360€	0.003	0.006***	0.013***
Other tenure	0.003	0.006***	0.005***
Household income (ref: null income)			
1st income quartile	-0.039***	0.006**	0.007***
2nd income quartile	-0.055***	-0.014***	0.001
3rd income quartile	-0.043***	-0.026***	0.002
4th income quartile	-0.046***	-0.037***	0.005*
Logarithm of savings	-0.001*	-0.002***	-0.002***
Log(potential MIS amount)	0.014***	-0.004***	-0.005***
Eligible population in municipality (ref: 1st quartile)			
2nd quartile eligible	-0.001	-0.000	-0.001
3rd quartile eligible	0.006		
4th quartile eligible	0.003	-0.001	-0.005**
Urban/rural municipality (ref: urban or intermunicipal pole)			
Belt municipality	0.002	0.003	-0.000
Intermediate municipality	0.004	0.001	-0.003
Peripheral municipality	-0.005	0.005	-0.001
Institutional Quality Index - IQI (ref: 1st tertile)			
2nd tertile of IQI index	0.004	-0.004	-0.000
3rd tertile of IQI index	-0.003	-0.006**	0.000
Income share ratio	-0.045	0.026	-0.002
Dropout rate	-0.082	0.171**	0.056
Proportion of crimes per 1000 inhabitants	0.030	0.130	0.065
Share of population attained tertiary education	0.030	0.047	-0.004
Employment rate	-0.002	-0.013	-0.006
Share of employed in construction sector	0.015	0.030**	0.010

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Share of employed in hotel/restaurant sector	-0.003	0.002	-0.001
Net export of municipality (ref: 1st tertile)			
Medium export level	-0.002	-0.002	-0.003
High export level	-0.002	0.004	0.003
Covid-19 cases in 2020	0.841***	-0.245	0.239
Exposure to 2020 companies' lockdown	-0.053	0.042	-0.078*
Regional level fixed-effect included	Yes	Yes	Yes
Observations	296,264	355,091	384,065
R-squared	0.627	0.764	0.790

Notes: as per table A3.

Table A6. Linear probability model predicting MIS receipt in the months of March 2021 (1), July 2021 (2) and December 2021 (3), for households in Southern Italy.

	(1) March 2021	(2) July 2021	(3) December 2021
Benefit recipient in 2019 or 2020	0.386***	0.128***	0.075***
Benefit recipient in February 2021	0.398***		
Benefit recipient in June 2021		0.751***	
Benefit recipient in November 2021			0.818***
Female	-0.002**	0.008***	0.007***
Age	-0.002***	0.000	0.000**
Age squared	0.000***	-0.000*	-0.000***
All household members above 67	-0.018***	-0.011***	-0.017***
Italian citizen	-0.013***	0.002	0.023***
Household type (Ref: Single)			
Single parent	-0.013***	-0.068***	-0.026***
Two adults	-0.022***	0.004***	-0.001
Two adults with one child	-0.025***	-0.074***	-0.034***
Two adults with 2 children	-0.029***	-0.087***	-0.030***
Two adults with 3+ children	-0.037***	-0.067***	-0.014***
3+ adults with no children	-0.038***	0.004**	-0.006***
3+ adults with one child	-0.033***	-0.068***	-0.032***
3+ adults with 2+ children	-0.037***	-0.068***	-0.018***
Permanent worker within household	-0.028***	-0.079***	-0.037***
Temporary worker within household	-0.020***	-0.036***	-0.019***
Self-employed within household	-0.017***	0.007***	-0.014***
Unemployed within household	0.006***	0.012***	0.006***
Inactive person within household	-0.002**	0.002**	0.000
Share of earners within household	-0.007***	0.009***	-0.007***
House tenure (ref: outright owner)			
Home owner with mortgage	0.017***	0.001	0.008***
Renter paying less than 3360€	0.001	0.008***	0.017***
Renter paying more than 3360€	0.003**	0.002*	0.019***
Other tenure	0.003***	0.005***	0.008***
Household income (ref: null income)			
1st income quartile	-0.032***	0.003***	-0.001
2nd income quartile	-0.040***	-0.015***	-0.009***
3rd income quartile	-0.032***	-0.024***	-0.011***
4th income quartile	-0.026***	-0.046***	-0.013***
Logarithm of savings	0.000***	-0.002***	-0.002***
Log(potential MIS amount)	0.019***	-0.002***	-0.008***
Eligible population in municipality (ref: 1st quartile)			
2nd quartile eligible	0.005***	-0.000	0.004***
3rd quartile eligible	0.006***	0.000	0.007***
4th quartile eligible	0.013***	0.007***	0.010***
Urban/rural municipality (ref: urban or intermunicipal pole)			
Belt municipality	0.004***	0.003**	0.002**
Intermediate municipality	0.000	0.004*	0.002
Peripheral municipality	-0.002	0.001	0.001
Institutional Quality Index - IQI (ref: 1st tertile)			
2nd tertile of IQI index	0.003**	0.004***	0.005***
3rd tertile of IQI index	0.001	0.005	0.005**
Income share ratio	0.080*	0.080	0.071*
Dropout rate	0.047	0.109***	0.073**
Proportion of crimes per 1000 inhabitants	-0.040	0.037	0.164**
Share of population attained tertiary education	-0.038	0.021	-0.001
Employment rate	-0.005	-0.025***	-0.013***
Share of employed in construction sector	-0.024***	0.000	-0.008

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Share of employed in hotel/restaurant sector	0.013*	-0.019***	-0.008
Net export of municipality (ref: 1st tertile)			
Medium export level	-0.002	-0.003**	-0.000
High export level	-0.002	-0.006***	-0.005***
Covid-19 cases in 2020	0.081	0.027	-0.050
Exposure to 2020 companies' lockdown	0.077	-0.046	-0.017
Regional level fixed-effect included	Yes	Yes	Yes
Observations	1,087,306	1,221,249	1,294,814
R-squared	0.606	0.715	0.770

Notes: as per table A3.

Figure A3. Take up of MIS in selected metropolitan cities.