Unpacking Welfare (Non-)Take-Up in Germany: Basic Income Support from Policy to Practice

Abstract

This article examines the fiscal implications of welfare (non-)take-up, highlighting how methodological choices influence welfare participation estimates. Using German survey data and linked administrative records, this chapter applies instrumental variable (IV) techniques and weighting methods to ensure robust and representative findings. It demonstrates how different modeling approaches—such as probit versus IV probit and weighted versus unweighted specifications—affect take-up estimates. This technical paper also emphasizes the importance of refining microsimulation models by incorporating regional rental market data to enhance the accuracy of welfare policy simulations. These insights contribute to a more precise assessment of welfare uptake and provide valuable implications for policy design.

JEL Codes: I3, J22, C18, I31
Keywords: welfare measurement, benefit take-up, estimation, methodology, microsimulation

Data Availability Statement

The analyses in this study are based on the German Socio-Economic Panel (SOEP), a restricted-access dataset. Access to the data can be obtained upon request from the SOEP Research Data Center at the German Institute for Economic Research (DIW Berlin).

Ethics Statement

This study uses secondary anonymized survey and administrative data. No additional ethical approval was required as no human subjects were directly involved.

Conflicts of Interest

The author declares no conflicts of interest.

0.1 Introduction

The (non-)take-up of welfare benefits has been a central focus of numerous studies (Bargain et al., 2012; Blundell et al., 1988; Chareyron and Domingues, 2018; Frick and Groh-Samberg, 2007; Gasior et al., 2019; Riphahn, 2001; Whelan, 2010; Wilde and Kubis, 2005) as it directly impacts the equitable distribution of resources and the effectiveness of social policies. A critical concern, however, is that significant distributional inequities may persist if non-take-up remains unaddressed, especially in the context of immigrants' impact on state budgets. Despite growing attention on welfare reforms, prior research has identified several methodological limitations in take-up calculations, affecting both poverty measurements and broader distributional outcomes (Riphahn, 2001; Bargain et al., 2012; Bruckmeier et al., 2021). This paper seeks to contribute to this area by addressing key methodological challenges, focusing on UBII in Germany and advancing the accuracy of welfare (non-)take-up estimation.

To advance this research, we employ a cross-model robustness exercise, demonstrating how different methodological choices—such as probit, IV probit, and weighted vs. unweighted specifications—can significantly affect take-up estimates. By contrasting these model specifications, our paper highlights the importance of methodological choices in welfare (non-)take-up studies. This contribution is novel in showing how commonly used models in the literature may lead to misleading conclusions if endogeneity and selection issues are not properly addressed.

Our analysis makes a crucial contribution by employing the German Taxes and Transfers Simulator Microsimulation Model (GETTSIM), demonstrating its unique potential as an open-source tool. This model, specifically designed for Germany's tax-transfer system, offers distinct advantages over existing microsimulation models (e.g., DIW-STSM and IAB-MSM). Its open-source nature enables broader applications and fosters future research on welfare benefits in Germany, addressing a significant gap where most existing models remain closed-source.

Furthermore, we strengthen the robustness of our analysis by comparing results derived from the IAB administrative data with those from the SOEP survey for the same years. This comparison offers insights into the consistency of different data sources for welfare research, allowing us to assess the reliability of survey data. The SOEP-CMI-ADIAB dataset, linking the German Socio-Economic Panel (SOEP) with administrative data from the Institute for Employment Research (IAB), provides a comprehensive resource for analyzing labor market behavior and social policy impacts. By combining detailed survey data with rich administrative records, it supports deeper analysis of individual and household outcomes, such as employment dynamics, income, and social benefits utilization.

Our study contributes to the broader literature on welfare (non-)take-up by addressing a major gap—presenting new estimates of non-take-up rates for 2017 and 2018, periods that have received limited attention in recent studies. This is particularly valuable as these years occurred prior to any significant economic shocks, offering new insights into how welfare take-up dynamics evolved during this period.

The non-utilization of basic income support benefits is a global phenomenon (see e.g., Bruckmeier et al., 2021; Chareyron and Domingues, 2018; Frick and Groh-Samberg, 2007; Gasior et al., 2019; Riphahn, 2001; Tasseva, 2016; Whelan, 2010; Wilde and Kubis, 2005). Policymakers have long been concerned about this issue, as means-tested benefits aim to ensure that vulnerable populations receive necessary support (Whelan, 2010). Low take-up rates undermine these objectives, potentially exacerbating poverty and hindering poverty reduction efforts (Bargain et al., 2012; Chareyron and Domingues, 2018). Hence, our study's findings have implications not only for improving the accuracy of welfare

(non-)take-up estimation but also for refining poverty and distributional measures, thereby providing valuable insights for researchers and policymakers.

This paper is structured as follows, Section 0.2 starts by discussing some literary works addressing the take-up (TU) or non-take-up (NTU) of welfare state benefits. Section 0.3 discusses our applied methods and data in more detail. Section 0.4 shows our results regarding the effect of methodology variations on the non-take-up estimates of UBII, known as basic income support. Overall, our findings support the substantiality of the methodology aspect in the estimation strategy. Finally, Section 0.5 tests the robustness of our results, and Section 0.6 concludes this paper.

0.2 Literature review

The persistent phenomenon of non-take-up of basic income support has been extensively documented, with substantial rates observed both in Germany and globally. For Germany, existing literature provides consistently high estimates: non-take-up rates for the period 2005–2007, based on monthly data, were estimated to range between 46% and 58% (Bruckmeier and Wiemers, 2012), while later studies covering 2005–2014, such as Harnisch (2019), utilized the DIW-STSM microsimulation model and the German SOEP survey to confirm similar patterns (an average of 55.7 per cent for the analyzed time period). This evidence underscores the significant and persistent nature of non-take-up.

The Hartz IV reform, implemented in January 2005 as part of a broader labor market reform package, marked a significant restructuring of Germany's welfare system. The reform merged unemployment assistance and social assistance into a single means-tested benefit, known as Arbeitslosengeld II (Unemployment Benefit II), aiming to simplify the system and incentivize employment. However, the reform also introduced stricter eligibility criteria and benefit reductions for certain groups, which may have inadvertently influenced non-take-up rates. Empirical findings further highlight that non-take-up of means-tested benefits is not uniquely German—where it is often referred to as Dunkelziffer—but also a widespread issue across Europe (e.g., Gasior et al., 2019).

0.2.1 Methodological discussion points

0.2.1.1 Definitions

As we observe, the definition of take-up varies significantly across studies, making direct comparisons of take-up rates challenging (see Chareyron and Domingues, 2018; Harnisch, 2019). This variability arises from many factors, including differences in how researchers define eligibility, measurement timeframes, and denominators in take-up calculations. As a result, measuring the non-take-up of benefits is a complex task that requires careful consideration of these methodological nuances (Goedemé and Janssens, 2020).

Two primary definitions of non-take-up emerge in the literature, each differing in the treatment of the denominator. For instance, Bargain et al. (2012) highlight two approaches, where one considers only eligible households that do not take up benefits, while the other expands the denominator to include those who take-up the benefits as well, despite appearing as ineligible.

$$NTU1 = \frac{E - T}{E}$$

$$NTU2 = \frac{E - T}{(E + M)}$$

where

E represents eligible households,

T denotes those who take up benefits, and

M represents households not eligible but observed taking up benefits due to due to erroneous assessment of their needs, other simulation errors or, indeed, administrative error (missed eligibility).

In addition to denominator-based variations, definitions also differ based on the welfare measurement timeframe. For example, Bruckmeier and Wiemers (2012) distinguish between 'temporary' and 'persistent' non-take-up. Temporary non-take-up refers to eligibility assessed at the time of a household survey, while persistent non-take-up evaluates eligibility over a longer period, such as a full year. This distinction is echoed by studies like Kayser and Frick (2001) and Harnisch (2019), which focus on monthly and annual measures, respectively.

The approach to calculating take-up rates also differs depending on the data and methodology employed. Some studies measure non-take-up in terms of benefit expenditures rather than caseloads. Gasior et al. (2019), for example, used a method combining official statistics and survey data to estimate non-take-up rates in Austria. However, such approaches are not without critique. Combining survey and administrative data, as in Gasior et al. (2019), has been questioned by Kayser and Frick (2001), who argued that inconsistencies between data sources could compromise the validity of the results. Similarly, Bargain et al. (2012) suggested reassessing denominators to account for non-regular social assistance cases or beta errors known as Type II errors as presented above, which further complicates comparability across studies.

Ultimately, differences in the measurement unit, time frame, and data sources highlight the methodological diversity in estimating non-take-up. While this diversity reflects the complexity of the phenomenon, it underscores the importance of clearly defining terms and methodologies to enable meaningful comparisons across studies.

0.2.2 Exclusions made and data weighting

A typical step in welfare recipient analyses is to exclude ineligible persons from the receipt of the respective welfare benefit, a practice followed explicitly in several related studies Bruckmeier and Wiemers (2018); Frick and Groh-Samberg (2007); Hancock and Barker (2005); Harnisch (2019). The exclusion criteria vary across studies (see Table A.1). For instance, Bruckmeier and Wiemers (2017) included only individuals aged 17 and older, and Frick and Groh-Samberg (2007) excluded asylum-seekers in special residences, students in student accommodations, and older people in nursing homes.[1] Similarly, Harnisch (2019) adopted a nearly identical approach to excluding certain groups, such as asylum seekers in special residences, students in student accommodation, and older people in nursing homes.

Germany saw its highest refugee influx in late 2015, with over a million asylum seekers arriving from 2013 to 2016, posing challenges for policymakers and researchers alike. For example, asylum-seekers are ineligible for Unemployment Benefits II (UBII), affecting the representativeness of welfare recipient data. The microsimulation model's validity and the SOEP's representativeness - respectively - are verified against national statistics in the first step (see Table A.2 for different welfare benefits and Tables A.3, A.4). While studies like Frick and Groh-Samberg (2007) and Tasseva (2016) have addressed underreporting

[1] Asylum-seekers in Germany are subject to restricted benefits under the Asylum Seekers Benefits Act (AsylbLG), students are generally excluded from regular social assistance. However, they can access education-specific support (BAföG), and older people in nursing homes rely primarily on pensions and long-term care benefits, with limited access to other social services.

in welfare data, these challenges persist in current data. In particular, we observe a clear underreporting of UBII recipients compared to official statistics in the SOEP survey, which may arise due to the exclusion of low-income groups from surveys as argued in the literature or of other ineligible groups (see Tables A.4 and A.5). For example, the representativeness of the data is further impacted by the exclusion of asylum-seekers which is discussed in our sample definition in subsection 0.3.1.[2] To address these arising issues, one proposal advised adjusting sample weights to ensure the representativeness of migrant groups, as suggested by Bruckmeier and Wiemers (2011), who adjusted sampling weights to compensate for excluded households in their analysis.

0.3 Methods and data

This section describes our data and the microsimulation model in use. Moreover, we explain how we combine survey data with the German tax-benefit microsimulation model in more detail.

We apply one of the established non-take-up definitions in the literature, denoted as $NTU1$ (Section 0.2.1.1), to calculate the non-take-up rate (NTR) of UBII. The dependent variable in our analysis is a binary indicator derived from SOEP data and a microsimulation model. The microsimulation predicts eligibility for the welfare benefit in question, while the microdata identifies whether the respondent has reported non-receipt despite eligibility as per the model's predictions. Thus, the variable equals 1 if the respondent reports not receiving benefits despite being eligible (eligibility is determined based on the microsimulation model).

$$\text{NTR} = \frac{(\text{Eligibility} = 1 \ \ 'MSM') \ and \ (\text{Take} - \text{Up} = 0 \ \ 'Survey')}{\text{All Eligible HHs (Eligibility} = 1 \ 'MSM')}$$

Regarding our operationalization, we focus on the stock of benefit recipients at a specific point in time, rather than on a flow of welfare recipients. This point in time corresponds to the month of the survey, and we employ a current point estimation approach. The microsimulation model prioritizes the benefits reported in the survey, specifically the Supplementary Child Allowance (SCA) and Housing Allowance (HA), to ensure accurate eligibility simulation as applied in practice. Furthermore, our wealth definition follows the SOEP household net overall wealth measure (SOEP 2007). In our robustness checks, we repeat the calculations while accounting for household net overall wealth, which includes vehicle and student loans.[3] In the means test of this benefit, part of the earned income is exempted as "allowable deductions" (referred to as 'Absetzbeträge'), and a certain amount of wealth is permitted based on household size. Additional discussion on the selection of wealth can be found in the Appendix A.1.1.

0.3.1 Data description

Our empirical analysis is based on the German SOEP dataset, a microdata household panel study collected in 2018 (SOEP, 2019). Based on the microsimulation models predictions, we estimate the non-take-up of the nationwide German basic income support program, Unemployment Benefits II (UBII), conditional on being eligible to receive this benefit. This latter information is predicted by the microsimulation model we employ. Furthermore, the simulation is based on households' income, work status, and

[2]Noting that this benefit is a household-reported benefit in the SOEP data, see variable hlj0032.
[3]Net overall wealth = household gross overall wealth - household total debts.

other needs-related characteristics reported in the SOEP for the working-age population between 17 and 64 years old.

Moreover, we exclude individuals categorized as “Asylum Seekers" or those holding a "Status of Tolerance" denoting a temporary suspension of deportation ("Duldung") from our sample. To ensure their comprehensive exclusion, we also eliminate individuals reporting any form of asylum benefit receipt. Furthermore, mirroring the methodology of Bruckmeier et al. (2021), we also opt to exclude students and apprentices due to their unique eligibility requirements for distinct types of benefits. Moreover, we drop the following ineligible groups for UBII receipt from our sample: those in education, pensioner, military, community service, apprentice or trainee, and student trainee or intern. After the applied sample exclusions, our unweighted sample size for the survey year 2018 consists of 12,891 HH heads, resulting in around 25.3 million households, of which 2.7 million are considered eligible for UBII, as per the estimations.

0.3.2 GETTSIM

Non-open-source models often dominate existing analyses of social benefits take-up in Germany.[4] In our analysis, the eligibility for the income support means-tested benefit is calculated by the German Taxes and Transfers simulator 'GETTSIM' microsimulation model (MSM)[5], an open-source MSM. GETTSIM simulates the German Taxes and Transfers System and estimates households' eligibility for UBII, in addition to other benefits, by calculating household and individual-level entitlements (*see* Table A.6). It allows for a near-complete simulation of the German taxes and transfers system, providing accurate estimations for years after 2005. The model replicates actual policy environments in Germany for many dates.

Additionally, GETTSIM supports changing policy scenarios, beyond the status-quo, as a feature for ex-ante policy reforms. As previously discussed, this paper employs the status-quo scenario, with no changes to policy parameters, to show the latest NTRs that could be estimated based on SOEP survey data before any economic shocks, thereby depicting the baseline scenario.

To elaborate on the different scenarios involved in the take-up analysis, we present a table depicting the four scenarios used in the analysis (see Table 1). These scenarios illustrate how eligibility, take-up, and non-take-up are modeled in both the MSM and SOEP framework:

Table 1: Depiction of the four different scenarios in a take-up analysis.

MSM (Full take-up)	SOEP (Observed take-up)	
	Yes=1	No=0
Eligibility		
Yes=1	Take-up	Non-take-up
No=0	Measurement Error	Ineligible

This table provides a simple depiction of the four scenarios: the full take-up model as simulated by the MSM and the observed take-up in the SOEP, distinguishing between actual take-up, non-take-up, ineligibility, and measurement errors.

The equation for a household's entitlement (HHE) level to the discussed benefit, UBII, represents the household's needs minus its current simulated income (or the household's adjustable income). The total needs are determined by the legally defined regular needs

[4]Examples include the ifo Tax and Transfer Behavioral Microsimulation Model (ifoMSM-TTL), DIW-STSM, or STSM-IAB.

[5] For the model documentation, see https://gettsim.readthedocs.io/en/stable/

of household members, additional needs, and housing costs:

$$HHE_i = HHN_i - HHY_i$$

Hence, according to the practice—also as implemented by the MSM—the household is UBII-eligible (=1) if its needs (HHN) exceed its income (HHY):[6]

$$HHN_i > HHY_i$$

0.3.3 Econometric set-up

Let HHE_i denote the simulated benefit or entitlement amount, and take-up can be expressed to occur ($P = 1$) if:

$$\mathrm{P} = \mathrm{I}\left(\beta_0 + \alpha_1 \mathrm{HHE_i} + \beta_2' \mathbf{x} + \nu_1 > 0\right) \tag{0.1}$$

where $\mathbf{I}$ (.) denotes the indicator function.

We are interested in α_1, which is the entitled benefit coefficient, for the instrumentation. HHE_i might be endogenous, so regression of P on $HHEi$ and Xi may yield a biased and inconsistent estimate of α_1. Previous literature discussed the potential endogenity channels that makes the simulated benefit amount endogenous if unobserved factors that influence the (non-)take-up decision are correlated with unobserved factors determining the household's labor supply, arguing that in this case, the simulated benefit amount would be endogenous because it depends on the household's simulated net income, which is a function of earned income. To account for this potential endogeneity, the entitled benefit (HHE_i) is modeled as an endogenous variable and expressed as a function of observed HH characteristics x, and the instruments z:

$$\mathrm{HHE_i} = \gamma_0 + \gamma_1' \mathbf{x} + \gamma_2' \mathbf{z} + \upsilon_2 \text{ where } (\upsilon_1, \upsilon_2) \sim \mathrm{N}\left(0, \sigma^2\right) \tag{0.2}$$

The benefit is modeled as a linear function of both the non-take-up decision characteristics and the instruments, $\mathbf{x}$ and $\mathbf{z}$, respectively, assuming the joint normality of the error terms υ_1, and υ_2.

And decomposing the entitled benefit amount, which is modeled as a linear function of the maximum level of benefits $b(x*)$, prioritized benefits over UBII[7] denoted by (t_y), and non-UBII income (y)

$$HHE \equiv \ HHE\ (y,\ x^*)\ = \overline{b}(\mathrm{x}^*\ ) - t_y\ - \mathrm{y} \tag{0.3}$$

Intuitively, this above equation should correspond to the MSM's function

$$\begin{aligned} \mathrm{HHE} \equiv \text{regelbedarf vermögenscheck}_{\mathrm{hh}} - (\text{unterhaltsvors}_{m_{hh}} \\ + \text{kindergeld}_{m_{hh}}) - \text{arbeitslgeld } 2_{eink_{hh}} \end{aligned} \tag{0.4}$$

The above equation Equation 0.4 translates into the following equation where all household (HH) variables are on a household level:

[6] This is subject to the additional condition that the household's wealth remains below the household-specific maximum.

[7] Examples of prioritized benefits are housing benefits and enhanced child benefits.

[7] This function sets benefits to zero if wealth exceeds the exemption threshold while arbeitslgeld $2_{eink_{hh}}$ function sums up the income per household to calculate basic subsistence. Therefore, this latter function should denote the HH allowable income.

$$\begin{aligned}\text{HHE} \equiv \text{Basic monthly subsistence level \& wealth checks} - (\text{Alimony advance payment} \\ +\text{Monthly child benefit}) - \text{Monthly subsistence payment per household}\end{aligned} \tag{0.5}$$

Where priority transfers correspond to the terms in the above bracket referring to aggregate monthly child support advance payment and monthly child benefits, both are on a household level (HH).

And given that the calculation of SGBII total simulated benefit should follow this equation, like what was depicted by Bruckmeier and Wiemers (2018):

$$\begin{aligned}\text{HHE} = &\text{ standardized regular benefits} \\ &+ \text{additional benefits due to special needs} \\ &+ \text{adequate housing costs} - \text{HH income and wealth}\end{aligned} \tag{0.6}$$

Equation 0.6 should thus mirror the following MSM's formula for the UBII benefit amount calculation:

$$\begin{aligned}\text{HHE}_{\text{GETTSIM}} \equiv &\ \text{Regelsatz}_{\text{m}_{\text{hh}}} + \text{Mehrbedarf} + \text{Kosten unter}_{\text{m}_{\text{hh}}} \\ &- \text{arbeitslgeld 2 eink}_{\text{hh}} \cap (W_i < W_{\max})\end{aligned} \tag{0.7}$$

Where W_i is the household wealth (discussed in more detail in the appendix, particularly subsection A.1.1), and $W_{\max}$ is the maximum allowable wealth.

0.3.4 The instruments

Regarding instrument selection in econometric analyses, it is crucial that the instrument does not correlate with unobservable factors influencing non-take-up decisions, such as motivations for work avoidance. At the same time, it must be correlated with the calculated benefit levels to satisfy the relevance criterion. Drawing on previous research (e.g., Whelan, 2010; Bruckmeier and Wiemers, 2012, 2016; Bruckmeier et al., 2021), we adopt the household minimum needs, or the monthly standardized regular benefits (B^R), as our instrument for determining the UBII benefit amount. In their analysis, Bruckmeier et al. (2021) define this as the level of regular benefit entitlement before individual income deductions (see Equation 0.6 and 0.7 above). This instrument meets the relevance criterion, as it is a key determinant of the benefit amount, which we will show in the results section.

In our analysis, the two instruments we use mirror those in Bruckmeier et al. (2021) (specifically, instruments (a) and (c) as denoted in their work). These instruments are likely uncorrelated with the unobserved factors that determine (non-)take-up decisions and, hence should be valid. In addition to the first instrument mentioned above, our second instrument is the monthly private transfers received by a household which consists of income received from persons outside the interviewed household. (e.g., alimony and child support payments or other payments), as reported in the SOEP.

$$\text{Cov}\,(\text{z},\ \text{v}_1) = 0, \text{ and } \text{Cov}\,(\text{z},\ \text{x}) \neq 0 \tag{0.8}$$

There are different implications when the entitlement amount is treated as endogenous. For example, the IV estimators (IV or 2SLS) remain consistent if the variable turns out

to be exogenous instead, though they can be much less efficient than the OLS estimator (Cameron and Trivedi, 2010). One indicator of endogeneity would be a loss in precision, evidenced by a considerable increase in the standard errors of the instrumented regressor when moving from OLS to IV.

The null hypothesis of the Wald test tests whether the regressor's simulated entitled amount is exogenous for the Durbin-Wu-Hausman test (*see* Cameron and Trivedi, 2010, p. 183). If the null hypothesis is not rejected, we cannot reject the exogeneity of the simulated amount in our model, and non-IV estimation should be unbiased and consistent in this case.

Several studies have addressed the issue of endogeneity, specifically focusing on the potential endogeneity of the entitled UBII benefit amount, also referred to as the household entitlement (HHE) (*e.g.,* Bruckmeier and Wiemers, 2012; Bruckmeier et al., 2021; Whelan, 2010). For example, Bruckmeier and Wiemers in their analyses explained that unobserved characteristics influencing the take-up decision are likely correlated with earned income (y) and thus with the benefit amount (b), which is based on income (y) and household characteristics ($\mathbf{x}^*$), see Equation 0.3. The authors further elaborated on this by providing an illustrative example of potential endogeneity. For instance, an individual's unobserved motivation to work or attitudes toward social assistance receipt, such as concerns about stigmatization, could impact the decision to take up benefits (or not, in our case) and subsequently affect their earned income. This is anticipated to influence the benefit amount included in the regressors of our model. As a result, the exogeneity of the benefit amount is likely violated in this case. Accordingly, our model has been formulated similar to the approach taken by Whelan (2010), Bruckmeier and Wiemers (2012), and the model configuration presented by Bruckmeier et al. (2021), all of which consider the potential endogeneity. This approach is particularly evident in our IV Models 3 and 4 presented in the table of regression results (Table 5) which we introduce next.

0.3.5 The models

Finally, we briefly introduce the various models presented in our regression section. Our dependent variable is a dummy variable that captures the non-take-up behavior. Hence, non-take-up is modeled in a discrete choice model following Blundell et al. (1988) or Bruckmeier et al. (2021), where proxies for costs and utilities of claiming the underlying social benefit are used. We show four models, the first two correspond to pooled probit regressions, both unweighted and weighted, respectively (Model 1 and 2), as displayed in Table 5. The next two models represent our IV estimated for both unweighted and weighted models, respectively (Models 3 and 4).

0.4 Results

0.4.1 Descriptives

Several noteworthy observations can be noted, based on our descriptive results. Our pairwise t-tests, conducted on the weighted sample of 2018, reject the null hypothesis that the NTRs of the EU migrant group are equal to those of natives, which contrasts with the findings of Bruckmeier and Wiemers (2016) who employed a similar migrant definition.[8] Meanwhile, the null hypothesis is not rejected for non-EU migrants compared

[8] Other studies like Harnisch (2019) did not differentiate between distinct migrant groups, thereby complicating a direct comparison of our migrant status-related findings with theirs.

to natives. Furthermore, echoing the conclusions drawn by Bruckmeier and Wiemers (2016), individuals possessing non-EU citizenship constitute a significant proportion of eligible households (as indicated in the last column of Table 2); their share among all eligible households reaches 22 per cent, implying a higher degree of welfare dependence among immigrant households. This pattern remains consistent with a more disaggregated demographic group distinction, i.e., even when refugees are treated as a separate category (Table 2).[9] This analytical step is crucial for investigating welfare dependency among migrant groups based on their migration status and citizenship. Notably, the NTRs of non-EU citizens surpass those of Germans when refugees are examined as a distinct category. Moreover, in our sample, we observe that the average of the simulated benefit amount is lower for the group who do not take up the benefit. The average amount for the non-take-up group (mean of 852.97) is lower than for the take-up group (mean of 1,142.22). This aligns with economic reasoning and consumer choice theory, suggesting that if the costs associated with claiming benefits outweigh the expected gains from the entitled amount, individuals may choose to forego benefits.

Table 2: Non-take-up rates of UBII in 2018 with a distinction for refugees.

Subgroup	NTU rates in subgroup	Share of eligible HH in subgroup	Share of all HHs	Share of all eligible HHs
Natives	40.8	8.6	88.1	69.8
EU-Citizens	55.2	14.2	5.0	6.6
Non-EU-Citizens	45.4	32.0	5.3	15.8
Refugees	24.0	73.3	0.92	6.2
All	**42.0**	**10.8**		

Notes: Temporary rates of non-take-up (results are shown for the wealth specification including vehicles). All shares are weighted. The fourth category of missing country information is not listed above (0.67% of total HHs). HHs are represented by household heads. Source: GETTSIM and SOEP v.36, for 2018.

0.4.2 Regression

We first discuss the effect of controls as observed in Table A.9. As we observe, the inclusion of controls significantly improves the model fit, as evidenced by the increase in pseudo-R^2, from 0.0450 to 0.181 in the unweighted model (and from 0.0287 to 0.249 in the weighted pooled probit model), highlighting the importance of these factors in understanding the non-take-up decision. All models in this analysis are estimated using robust standard errors.

Next, we demonstrate how different estimation methods affect the results by highlighting their connection to the representativeness of our analyzed sample. Before presenting our regression findings, we perform macro-validation checks to ensure the robustness of our approach (see Tables 3 and 4 below). Representativeness is critical for obtaining methodologically sound results that accurately reflect the broader population and is a crucial starting point in the analysis. This accuracy is particularly important when evaluating the fiscal impact of non-take-up, as it involves comparing actual benefit expenditures from macro-statistics with simulated ones. For this reason, our preferred model is the IV weighted model (Model 4). We will explain why this model is especially well-suited for interpreting our results.

Furthermore, in our regression results displayed in Table 5, we observe almost similar point estimates of models (1 and 3, the unweighted probit and the unweighted IV probit). We also observe the amount of benefit, the suspected to be endogenous appears statistically

[9] This classification encompasses categories 2, 3, 4, 6, and 7 of the actual residence permit SOEP variable, encompassing groups such as (in German): Asylberechtig, Fluechtlingseigenschaft, subsidiaerer Schutz, humanitaere Aufnahme, and Familiennachzug.

insignificant in our last displayed model (Model 4, the weighted IV probit), where the standard errors have increased.

Table 3: Frequency Distribution of 'nationality' (Unweighted)

Nationality	**Freq.**	**Percent**	**Cum. Percent**
GER	1,657	30.67	30.67
EU	284	5.26	35.93
Non-EU	3,460	64.05	99.98
Missing country info	1	0.02	100.00
Total	5,402	100.00	100.00

Table 4: Frequency Distribution of 'nationality' (Weighted)

Staatsangehoerigkeit	**Freq.**	**Percent**	**Cum. Percent**
GER	3,692,078.9	70.18	70.18
EU	381,259.73	7.25	77.43
Non-EU	1,186,897	22.56	99.99
Missing country info	362.86	0.01	100.00
Total	5,260,598	100.00	100.00

In Table 5, the results of the IV models suggest that while the unweighted IV probit model (Model 3) meets the standard requirements for instrument relevance and exogeneity, as indicated by the first stage statistics, endogeneity tests and overidentification tests, it is not the preferred choice for the final interpretation. This is primarily due to the failure of the unweighted model to account for population distributions, which could lead to selection bias, a concern that becomes evident when comparing sample statistics between the unweighted and weighted samples (Tables 3 and 4). The unweighted and weighted frequency distributions of nationality suggest a skewed distribution, particularly in the unweighted dataset, which is heavily skewed towards "Non-EU" nationality. On the other hand, in the weighted data, the skewness issue is reduced, with Germans forming the majority of population. Having this said, weighting is crucial in this context. As a result, the weighted IV probit model (Model 4) becomes the focus of this analysis.

Furthermore, we justify the selection of the IV weighted model on several grounds. In the weighted model, endogeneity and weak instruments are not significant concerns, as shown by the overidentifying restrictions test, which suggests some validity of the instruments, and the robustness of the endogeneity tests, with p-values indicating no major issues.[10] The strong first-stage statistics of the IV weighted model (153.926 ρ value of 0.0000) further support the relevance of the instruments. We believe these instruments are valid, as the literature previously has shown (e.g. Bruckmeier et al. 2021), they are uncorrelated with the error term and correctly excluded from the estimated equation. Given these results, the weighted IV probit model is deemed more reliable than the unweighted model. This speaks for selecting the last model (weighted IV probit) as our preferred model for which we interpret the results.

Notably, controlling for migration background does not reveal any statistically significant difference in the non-take-up probability between the different migrant groups (EU

[10]Among the weak instrument tests, we prefer those that account for weights, such as the Lagrange Multiplier (LM) method-based CLR and K-J tests. Test results in detail are: the weak instrument tests for the weighted IV probit model suggest that the instruments are not weak. The CLR and K-J tests yield p-values of 0.1324 and 0.1336, respectively, indicating no evidence of weak instruments. The J test shows a p-value of 0.1760, and the AR test yields a p-value of 0.1299, further supporting the validity of the instruments. The Wald statistic is 2.51 with a p-value of 0.1134, suggesting that the null hypothesis of no effect cannot be rejected. The confidence intervals for the estimated coefficients lie within the range [-0.000273, 0.000116], and the tests are robust to heteroskedasticity. Overall, the tests confirm the strength and validity of the instruments used in the weighted IV probit model.

and non-EU, respectively) compared to natives. This suggests that the non-take-up behavior of migrants is not notably different from that of natives. The signs of the respective migration coefficients align with earlier findings in the literature (Bruckmeier and Wiemers, 2016). The pattern has not changed when we compare our results to the latter study, at least in terms of the signs of the migration group coefficients.

Turning to the results of our preferred model—the IV weighted regression—we cannot reject the null hypothesis that $\alpha_1 = 0$, as shown in Table 5 (see Equation 0.1). In contrast, models without weighting or without the IV reject the null. The IV in the weighted model reduces the point estimate of α_1 and increases its standard error, consistent with addressing endogeneity bias.

Following the recommendation of Solon et al. (2015), we report both weighted and unweighted estimates to provide a deeper interpretation of the results. In many situations where weighting is advisable, robust standard error estimates should also be applied, which we have ensured. Based on our results, without weighting, the IV estimate of the monthly simulated benefit amount remains marginally significant; however, we place less confidence in this result due to selection issues in the unweighted sample. These findings suggest that studies failing to account for both endogeneity and selection bias through IV and weighting may have wrongly rejected the null. Thus, the evidence for α_1 being significant is weak, highlighting the importance of addressing these biases for robust inference.

Table 5: Marginal effects of non-take-up decision (temporary non-take-up at means)

	(1) Unweighted Probit	(2) Weighted Probit	(3) Unweighted IV Probit	(4) Weighted IV Probit
Panel A				
Dep. var: Non-Take-Up of UBII				
Simulated UBII benefit amount (in euros)	-0.000245***	-0.000438***	-0.000210*	-0.000317
	(0.0000493)	(0.000112)	(0.0000955)	(0.000182)
EU-nationality (Ref. Germans)	0.272**	0.258	0.258**	0.255
	(0.0875)	(0.133)	(0.0880)	(0.133)
Non-EU nationality	-0.389***	-0.142	-0.313***	-0.0984
	(0.0565)	(0.0997)	(0.0603)	(0.103)
Panel B: First Stage Regression				
Simulated UBII benefit amount (in euros)	-0.711***	-0.922***		
			(0.0393)	(0.0719)
Monthly private transfers			0.604***	0.613***
			(0.0211)	(0.0389)
Controls	✓	✓	✓	✓
First-stage F-stat.	512.58	-	153.9	-
Kleibergen-Paap Wald F-statistic F(2,4211):(p-value)	(0.0000)		(0.0000)	
N	5400	5400	4239	4239

Standard errors in parentheses.* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
List of controls includes: age, age^2, married, education levels, employment status, homeowner, single-parent, disability dummy, female, residence (east/west), city size, has children dummy.
Instrument Test Results for Unweighted IV Probit:
Endogeneity Test (Robust Score chi2): 1.988 (p-value = 0.1585).
Endogeneity Test (Robust Regression F-statistic): 1.942 (p-value = 0.1635).
Overidentification Test (Score chi2): 3.180 (p-value = 0.0745).

0.5 Robustness

We perform several sensitivity checks. First, we test our results using three instruments rather than the only two we described above in subsection 0.3.4. We add another conventional instrument employed in the literature: non-earned public transfers, specifically, the monthly amount of household social security pensions received. Our results remain roughly the same (see Table A.10).

Second, in the subsequent subsections, we run two quality checks. First, we assess the microsimulation quality in subsection 0.5.1. Second, we implement flat changes as part of our robustness checks to some of the key variables. Third, in subsection 0.5.2, we check to what extent the UBII reporting in the SOEP data aligns with the administrative records.

0.5.1 Q-Q plot

In this section, an assessment of the simulation quality is performed using the quantile-quantile Q-Q plot (Figure 1). We find that our applied MSM overestimates benefit amounts, similar to the results observed by Fourrier-Nicolaï (2020), who used a microsimulation model.[11] However, in contrast to his estimation strategy, we do not follow a yearly simulation approximation but instead base the estimations on monthly data. The author argued that his technique after converting data into annual data might explain why the benefit amount was overestimated. Moreover, we find that 81% of the observed receivers are simulated as being eligible. Such level has been indicated by Fourrier-Nicolaï (2020) as a reasonable level of quality for a micro-simulation model, which is connected to the discussion by Bargain et al. (2012) on the accuracy of microsimulation methods.

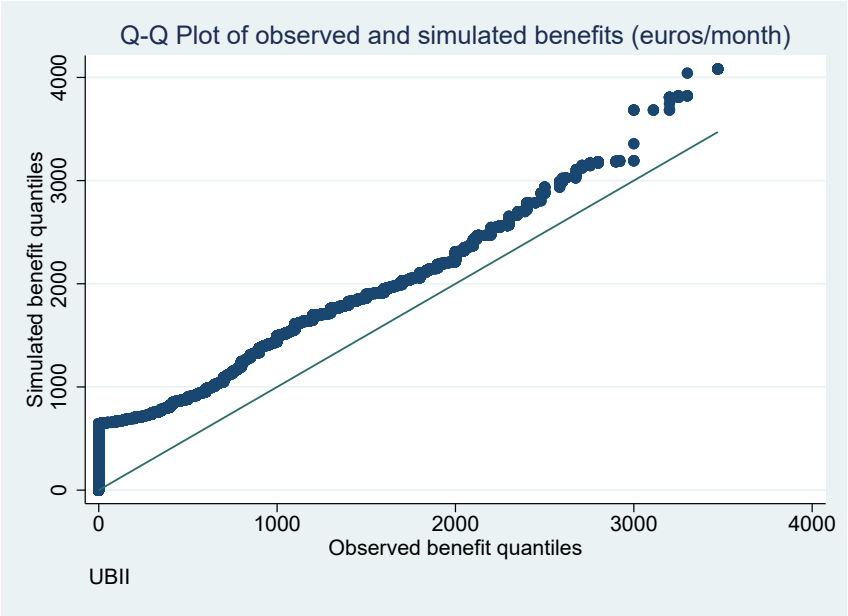


Figure 1: QQ-plot

[11] Fourrier-Nicolaï (2020)'s microsimulation model is based on a simplified procedure of the STSM-IAB model adapted for the GSOEP that is extensively described in Bruckmeier and Wiemers (2012).

0.5.1.1 Flat variations in the key variables

The following equation of household's entitlement (HHE) level depicts the household's needs minus its current simulated income or the HH adjustable income where the total needs are determined by the legally defined regular needs of HH members, additional needs, and housing costs.

$$HHE_i = HHN_i - HHY_i$$

Hence, the HH is UBII eligible (=1) if the household needs exceed their income:[12]

$$HHN_i > HHY_i$$

In our sensitivity checks exercise, we use the following two alterations where x represents here the per cent of variation introduced to the original estimate (i.e., 5, 10%):

$$HHE_i = HHN_i - HHY_i\,(1 \pm x)$$

$$HHE_i = HHN_i\,(1 \pm x) - HHY_i$$

Next, we provide estimates of the extent of non-take-up rates by changing the model's specifications given some flat variations in the key variables affecting the means test; income, needs, and housing costs (Table A.11). The three variables are determinants of eligibility in the means test. Variations of $\pm 5\%, \pm 10\%$ are included in these three variables as a standard check. Moreover, GETTSIM provides current and past policy environments and allows users to alter policies by changing parameters, and we exploit this feature to check for the sensitivity of the needs condition. The main aim of this exercise is to absorb any deviations in the reported amounts from the correct values. Likewise, Chareyron and Domingues (2018) discussed that the major assumption made in their study concerns the correct declaration of income, and therefore assessed how this assumption influences their results by estimating model with a 25%, a 10%, and a 15% change in income, following Bargain et al. (2012).

0.5.2 Cross-checks using administrative linked data

This section demonstrates the robustness of the analysis by cross-checking survey data from the SOEP with administrative-linked data from the IAB. While it is widely acknowledged that households tend to under-report benefit receipt in surveys, this comparison provides evidence that the reported take-up rates in the SOEP align closely with administrative records. By validating the survey data against a more precise benchmark, the analysis establishes the reliability of the SOEP as a valuable source for studying benefit take-up. This strengthens the case for using survey data in contexts where administrative data may not be available or fully accessible or when administrative data have a limited sample size.

Along with the SOEP survey data, we exploit the linked administrative data with the SOEP survey in this section, especially since actual welfare receipt is observed in administrative data. We extend our analysis by employing the relatively recently released (SOEP-CMI-ADIAB, version 7520) which is jointly provided by the German SOEP and the Institute for Employment Research (IAB) (Antoni et al. (2023b)). This data report describes the data product "Survey data from SOEP-Core, the IAB-SOEP Migration Sample, the IAB-BAMF-SOEP Survey of Refugees, and the SOEP Innovation Sample linked with administrative data from the IAB." Specifically, the administrative data

[12] Along with the condition that the HH's wealth remains below the household-specific maximum.

originate from the IAB's Integrated Employment Biographies (IEB). For documentation, see Antoni et al. (2023a). This administrative data contains information on personal characteristics, information on employment, benefits, job search and participation in labor market measures, residence characteristics, and technical characteristics.

We are particularly interested in the receipt of benefits per Social Code Book II (SGB II) recorded from 2005 onwards, and verifying its receipt based on linked data. This latter contains information about survey respondents who consented to data linkage and were registered with the Federal Employment Agency (Bundesagentur für Arbeit - BA) or at an institution responsible for implementing SGB II as job-seekers. Former research work by Eggs (2016) has explained, that the linkage would fail, for example, if survey respondents are genuinely not included in the administrative dataset, and the latter is the case for all persons who have never been unemployed, received UBII, officially searching for a job, or in employment subject to social insurance contributions (i.e. they have been students, housewives/men, self-employed or federal employees all their life).

Consequently, we keep only successfully merged cases and information related to spells of Unemployment Benefit II Recipient History (Leistungshistorik Grundsicherung - LHG) in our dataset used for detecting misreporting.[13] We follow a quite similar procedure analogous to other studies (Bruckmeier et al., 2021, 2018; Eggs, 2016; Meyer et al., 2022; Mittag, 2019) that compared survey data with administrative microdata. To explain, our analysis compares information the respondents provided on UBII's current receipt in the SOEP with the information on UBII's receipt in the same month and year gained from the LHG records. We link survey data with administrative records on the individual level using the personal identifier and the month of the year (date of the LHG spell and survey year and month of interview). In our case, similar to Meyer and Mittag (2021), this matching is possible because the reference period in the survey is clearly defined and the administrative data contain detailed information on the time of receipt. The SOEP asks respondents whether they receive the basic income support benefit within the same interview month.[14] We ended up with 161,421 successfully merged year-person observations.[15]

Table 6 shows our results when the receipt of the benefits information in the SOEP survey is validated using the administrative-linked data in ADIAB.[16] According to the documentation of this linked data, 26,767 persons through the year 2020 have given consent to the data linkage concerning our analysis sample (excluding SOEP IS).[17] As discussed, the technique followed is to link up each survey response on welfare receipt with the administrative records whose episodes overlap the response month of the given survey year.[18] The comparison we conduct, based on all available years in our linked data, yields several confirmed cases regarding the basic income support benefit receipt across both data sources (i.e., where the reported benefits in the survey data match the information in the administrative data). Around three quarters show consistent

[13]The data documentation explains that the receipt of benefits per Social Code Book III (SGB III) and Social Code Book II (SGB II) is recorded in the Benefit Recipient History (Leistungsempfängerhistorik - LeH) and the Unemployment Benefit II Recipient History (Leistungshistorik Grundsicherung - LHG). Moreover, the LHG source covers the data over the period 01.01.2005 - 31.12.2020.

[14]See https://www.diw.de/documents/publikationen/73/diw_01.c.866901.de/diw_ssp1206.pdf

[15]And 629,685 for when (merge=2) after we started with administrative data as our master dataset and keeping all spell types. The code is available upon request.

[16]The exclusion criteria necessitates dropping cases if _merge== 1 Since _merge == 1 cases lack corresponding survey responses, they might not contribute to the misreporting detection process that relies on cross-validation. These cases should correspond to the SOEP-IS innovative survey while in our study we apply only the SOEP-Core which justifies our dropping decision.

[17]I.e., constituting (SOEP Core, Mig, Ref), see data documentation p.34.

[18]The administrative variables will be unmatched for those with no such administrative records (i.e., have given no consent or not found in administrative data or for other reasons). This enables us to calculate the variable confirmed, indicating whether the survey response agrees with the administrative records.

reporting in survey data aligning with administrative data. Based on other survey data, it was discussed that there is growing evidence that program receipt is badly reported in household surveys (Meyer et al., 2022).

To further inspect the level of consistency related to our sample selection criteria, we restrict the validation results to household heads only and the survey years studied in our paper (2018 and 2017); this results in 3,842 consistent cases (about 72%) vs. 1,530 cases (about 29%) which leads to a total of 5,372 cases. We cannot however inspect further if these observations are particularly the ones analyzed in our regression sample because any merging of microdatasets is not allowed and GETTSIM is not installed as one of the working tools available for use within the regional data SOEP visits.

The previous discussion by Meyer et al. (2009) highlighted how surveys with different question timing should shed some light on the reasons for misreporting. In our case, because we use the question on the current UBII benefit receipt, this could make the reasoning of forgetting about the receipt of the benefits as one explanation in our context less superior. We proceed by addressing misreporting through a data validation procedure and investigating the extent of underreporting, particularly in the aggregate linked data. Underreporting is identified based on the month of the interview. Table 6 below shows underreporting cases as those cases listed in the reference category (6,407), and they shrink to 1,530 observations out of 5,395 when the criteria are restricted to our analysis years and household heads only. This type of error has received much attention in the literature and is interpreted as underreporting of UBII benefit receipt by true recipients (the true false negative rate, p_{10}).[19]

Table 6: Confirmed cases regarding UBII benefit reporting in both data sources (SOEP survey and ADIAB administrative linked data - for all available survey years until 2020

Confirmed cases through data linkage	Freq.	Percent
0	6,407	25.79 %
1	18,432	74.21 %
Total	24,839	100 %

Note: Own calculations based on SOEP v37 and SOEP-CMI-ADIAB 7520 (v1). 1 refers to the UBII receipt confirmed observations in the admin. data. Zero refers to contradictions across both data sources (i.e., benefit underreporting).

0.6 Concluding remarks

This paper highlights that studies failing to account for both endogeneity and selection through IV and weighting may have mistakenly rejected the null hypothesis, particularly in relation to the welfare benefit amount of UBII α_1. Therefore, future research should consider both weighting and IV methods to ensure robust and accurate inferences about welfare (non-)take-up behavior, especially when the population sample is non-representative in the absence of weighting.

The paper also discusses the methodological considerations crucial for modeling the (non-)take-up of welfare benefits, emphasizing the importance of clearly defined analysis steps and exclusion criteria. To improve estimates, it is necessary to standardize procedures for calculating non-take-up, as suggested by previous studies (e.g., Riphahn, 2001). A key avenue for future research involves comparing non-take-up estimates across different microsimulation models (MSMs), as well as examining the implications of using weighted

[19] An informative representation of the type of errors can be found in the supplementary data of Meyer et al. (2022), under the title ´´Bias in Error Rates with Misclassification in the Administrative Measure."

versus unweighted models (see Solon et al., 2015). The weighted model is essential for ensuring representativeness and addressing selection issues, as it accounts for the actual population distribution, unlike the unweighted approach. In particular, the underrepresentation of the foreign population, as noted by Kayser and Frick (2001), warrants further attention and comparison of results before and after exclusions. Future research should involve cross-model and cross-dataset comparisons, such as between the IAB-MSM and GETTSIM, and examining the impact of weighting on model outcomes to assess the robustness of welfare take-up estimates. Furthermore, this study suggests that a more explicit handling of wealth, migrant definitions, imputation methods, and exclusions would contribute to more accurate estimates.

Another important research avenue involves addressing the limitations posed by the lack of regional location data in current datasets, as highlighted by Gasior et al. (2019). Incorporating regional rental market data, particularly for housing allowances, could enhance the precision of simulations, bringing them closer to administrative datasets and improving the comparability of estimates. This approach would refine the estimation of NTRs by accounting for regional variations in rent levels and homeownership policies. Such improvements are essential to advance the development of more accurate welfare uptake simulations, ultimately contributing to more robust policy evaluations.

Appendix A

Appendix to Chapter 2

Table A.1: Methods applied in some selective non-(take-up) analyses

Source	Year/Unit	Mean ALGII	Weighted descriptives	Weighted regression	MEs
Bruckmeier & Wiemers (2011)	2005	499 €			
	2006	508 €	✓	x	Not reported
	2007	478 €			
Bruckmeier & Wiemers (2016)	Natives	479 €			
	EU-Migrants	502 €			
	Non-EU-Migrants	585 €	✓	x	Average marginal effects
	Migrants with German citizenship	505 €			
Bruckmeier & Wiemers (2018)	Household	794 €	✓	x	Not reported
Bruckmeier & Wiemers (2021)		714 €	x	✓(in sensitivity checks)	Not reported
Whelan (2010)		666 €	x	x	At means
Frick & Groh-Samberg (2007)	Simulated households (SOEP)	464 €	x	x	Not reported
	Official Statistics	413 €			

Table A.2: Non-take-up rates and measurement errors of other simulated social benefits in Germany in 2018

Simulated Benefits (2018)	**NTRS**	**Measurement errors**
Housing Allowance, HA	93.79%	24.8%
Supplementary Child Benefits, SCA	90.76%	26%
Child Benefits	3.86%	19.8%

Notes: Own calculations based on GETTSIM and the SOEP. Housing Allowance denotes the German "Wohngeld", Supplementary Child Benefits denote "Kinderzuschlag", and Child Benefits denote "Kindergeld." The former two benefits; Housing Benefits and Enhanced or Supplementary Child Benefits are prioritized benefits.

Table A.3: Comparison of simulated and official UBII statistics (2018, before sample exclusions)

2018	**UBII Recipients (Needs Units)**	**Individuals in Needs Units**	**Annual UBII Amount (€)**
GETTSIM (Simulated)	3,197	10,411	39,110.26 (Obs: 3,182)
GETTSIM (Weighted)	3,642.29K	7,949.01K	31,278.18M
BA (Official Statistics)	3,093K	6,066K	28,988.75M
Coverage (%)	117.8%	131%	108%

Note: BA refers to the German Federal Employment Agency (Bundesagentur für Arbeit). Figures are in thousands (K) and millions (M) where applicable.

Table A.4: UBII benefit receipt in the SOEP and official statistics in 2018 (after sample exclusions)

2018	**Recipient of Regular UBII (Needs Units)**	**People in Needs Units**	**Annual amount of Regular UBII (thousand €)**
SOEP (observed)	2,316	8,541	23,710.812
SOEP (weighted)	2,122,228	4,620,915	18,738,358
SOEP (imputed retrospective)*	2,738,928	6,112,937	22,233,215
BA official statistics (2)	3,092,540	6,065,578	28,988,754
SOEP Coverage (% = 1/2)	68.62%	76.18%	64.64%

Notes: * refers to specification b of our estimations as explained in Table A.11. BA refers to the German Federal Agency for Employment (Bundesagentur für Arbeit).

Table A.5: Benefit receipt of UBII in SOEP and official statistics in 2017 (after sample exclusions)

2017	**Recipient of Regular UBII (Needs Units)**	**People in Needs Units**	**Annual amount of Regular UBII (thousand €)**
SOEP (observed)	2,690	9,900	24,316.908
SOEP (weighted) (1)	2,350,227	5,306,562	19,534,906
BA official statistics (2)	3,262,236	6,317,062	30,061,782
SOEP Coverage (% = 1/2)	72.04%	84%	64.98%

Notes: * BA refers to the Federal Agency for Employment, and BA expenditures refer to the two items (ALGII/Sozialgeld + Kosten der Unterkunft).

Table A.6: GETTSIM microsimulation features

	Sign	Income components	Determined in GETTSIM tax and transfer model?
1	+	**Earned income**	No
	+	Self-employed income	No
	+	Capital income	No
	+	Rental income	No
	+	Other incomes (pensions)*	No
2	-	**Social security contributions** (Old-age pensions + employee unemployment insurance + employee health insurance)	Yes
	-	Income tax	Yes
	-	Capital income tax	Yes
	-	Alimony advance payments	Yes
3	+	**Child benefit**	Yes
	+	Child-raising allowance (Child enhanced or additional Income)	Yes
	+	Unemployment benefits (no endogen. labor supply)	Yes
	+	Maternity allowance	Yes
4	+	**Housing allowance (HA)**	Yes
	+	Supplementary child allowance	Yes
	+	Social assistance for employable persons (SGB II)	Yes
	+	Social assistance for unemployable persons (SGB XII)	No**
	=	**Net household income**	No

Notes: *The model predicts the updated earning points for pension claims. **The model might have introduced further predictions in the most recent version. Supplementary child benefits (Kinderzuschlag) is also referred to as Child Enhanced or Additional Income.

A.1 Further notes on the methods applied

A.1.1 Selection of the household net worth

Little is known about the handling of wealth in the take-up analyses despite its importance. The current state of the literature shows that addressing it has been mostly overlooked. Moreover, welfare analyses account for wealth differently in practice, calling for a more unified framework. Table A.7 provides evidence on the heterogeneous handling of wealth in the non-(take-up) analyses (Bruckmeier and Wiemers, 2012; Frick and Groh-Samberg, 2007; Fuchs et al., 2020; Harnisch, 2019).

In the context of unemployment benefits II, a means-tested benefit in Germany, the relevant wealth is the household wealth since the unit of analysis should be "community of need," which is often assumed to be at the household level. The German Socio-Economic Panel (SOEP), since 2002, has attempted to fill this gap by collecting information on private household wealth, providing new insight into this important issue (Westermeier and Grabka, 2015). Wealth information is substantial input to model the social benefits' eligibility of the respective units.

Due to the sensitivity of wealth information, possibly leading to a high share of missings, the SOEP has taken advantage of surveyed wealth data points for improved imputation strategies. Accordingly, this offers possible ways of estimating welfare eligibility since it offers multiple options for imputed wealth. The SOEP provides information on HH's

(household) overall wealth, among other possibilities.[1] Similar to Boertien and Lersch (2021), one variable of interest is total net household wealth (all assets minus debts and loans). Assets include real estate, financial assets, life insurance, private pension plans, and businesses. Debts include mortgages, loans, and other debts. The EVS is one comparable survey used in take-up analyses. By contrast, according to Riphahn (2001), the considered items in the EVS describe the sum of building society savings agreements, bonds, shares in mutual funds and stocks, savings accounts, other financial assets, and the sum of checking account balances which may be negative.

One can use only one imputation for initial model building and preliminary analyses. However, using all five imputations in a multiple imputation framework is recommended for the final models, where variance within and between imputations is considered.[2] Five implicates are created, and "mi estimate" commands are used to obtain standard errors for final estimates that consider imputation's uncertainty (Meriküll and Rõõm, 2022).

Another problematic aspect is that knowledge is limited on whether we should account for household-owned vehicles. Besides, some items would not count for calculating UBII's accountable income and are called exempted assets, such as vehicles below a certain value would be exempted in the means test. UBII applicants could keep up to certain amounts in their passbook savings when receiving the income support benefit. How to account for vehicles in estimating UBII eligibility has been raised by Riphahn (2001) for instance.

Since wealth modules are available in the SOEP every five years starting from 2002, we select the year for which we have wealth information to compare the model's outcome to previous literature's results. This means we inspect the results for 2017 and compare the result to that of Bruckmeier and Wiemers (2011). Regarding the HH's wealth as one determinant in the means test, the reference here is to check the household's needs against the following items:

- HH net income and HH wealth (where some authors follow the approach of proxying financial assets by HH capital income: Yk[3])

The procedure for UBII applications requires reporting the assets of all members of the applicant's benefit community ('BG'), whether in Germany or abroad. Assets include banking and saving accounts, cash, equities, bonds, claims, vehicles, building savings agreements, private pension insurance funds, developed or undeveloped real estate, and owner-occupied apartments. Up to certain amounts in passbook savings could be retained when receiving income support benefits. Additionally, some items do not count toward UBII's accountable income and are classified as exempted assets. For instance, vehicles below a certain value are exempt from the means test.

A.1.2 Exploiting the regional Data

Simulated benefit eligibility depends not only on household income and needs but also on precise regional location. This regional aspect is often overlooked in take-up literature, particularly regarding how regional assignment is managed. An accurate identification of regional location poses challenges due to gaps in available data. As Blömer and Peichl (2020) argue, missing information on local rent levels often necessitates using weighted averages of rents, capped by legally defined maximum support levels, to approximate housing benefit entitlements.

[1] HH net overall wealth (w011Hx = w010Hx - w001Hx; imputation alternative x = a,b,. . . , e) which equals HH gross overall wealth minus HH overall debts. And for the influence of the imputation or editing process (household level, weighted) on overall net wealth (see Frick and Groh-Samberg (2007), Table 11).

[2] We thank Philipp Lersch for the note.

[3] This method has been applied by Fuchs et al. (2020), for example.

For instance, housing allowance (*Wohngeld*) calculations account for household size and regional housing price levels. This interplay highlights the critical role of accurate regional assignment in simulating eligibility for housing benefits. The housing cost predictions in microsimulation models rely on such regional rent-level data, typically categorized into seven "rent levels" (*Mietstufen*). These levels are assigned based on the district and municipality of the housing unit eligible for this benefit. In the microdata used, the SOEP provides regional data variables. However, due to the broad categorization of the SOEP's regional policy regions (*Ror96 classification*), a precise match with state-specific classifications remains challenging. As a result, this analysis assumes a national average housing benefit level when regional data cannot be directly matched. Such assumptions, while necessary, underscore the importance of improving regional granularity in future simulations.

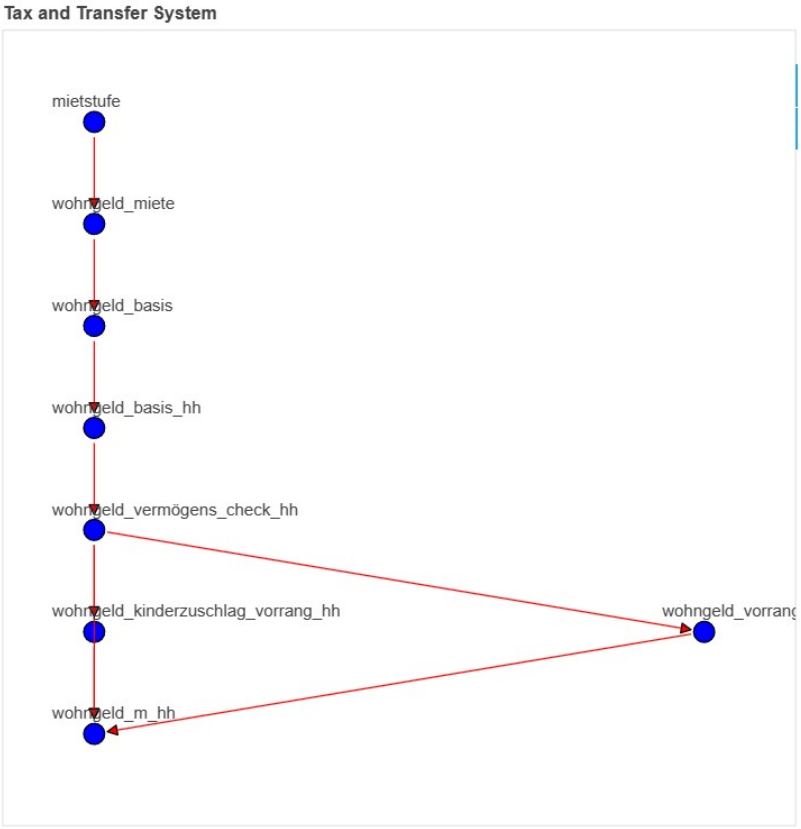


Figure A.1: Variables related to the rent level input variable

Ideally, integrating rent-level information into the SOEP variables would significantly enhance the accuracy of welfare benefit simulations. Comprehensive data would provide deeper insights into the determinants of welfare take-up; however, surveys often lack critical information (Duclos, 1995).

A notable limitation highlighted by Fuchs et al. (2020) is the inability of the residential status in the data to facilitate clear regional assignments, which are crucial for determining eligibility. Given that housing allowances depend heavily on local rental markets, incorporating rent levels from different municipalities could improve estimation accuracy. This would be feasible if the SOEP allowed for precise regional or municipal simulations. To address this limitation, harmonizing survey data with official rent level information published by states—categorized by municipal rent tiers—would be a significant step forward.[4]

[4]See,https://www.bmwsb.bund.de/SharedDocs/downloads/Webs/BMWSB/DE/veroeffentlichungen/wohnen/wohngeld-2023/mietstufen-2023.html

This refinement would improve simulation results for several reasons. First, it would enhance the accuracy of upper limits for housing cost estimations, as these limits vary by region. A more precise regional assignment would also improve the comparability of take-up results with regional administrative datasets, leading to more accurate non-take-up or take-up estimates. Additionally, the impact of homeownership on eligibility is crucial; certain income support recipients may be allowed to own homes, depending on local rental costs (Riphahn, 2001). This highlights the importance of aligning the simulated housing costs with actual regional means-test parameters, ensuring accurate eligibility determinations for basic income support.

To further improve the simulation quality, a useful tool is the rent level data sheet published by federal states since January 1, 2016, which assigns the correct rent level based on the district of residence.[5] The Institute for Housing and Environment also provides detailed listings of rent levels for various periods (IWU, 2020).

[5]https://www.iwu.de/forschung/gebaeudebestand/misimko/statistikdaten/

Table A.7: Wealth specification in a selection of the non-(take-up) literature

Study	**Survey Year(s)**	**Wealth Checks**
Frick & Groh-Samberg (2007)	2002	- Gross worth of other properties minus possible debt on other properties - A rather high threshold is applied (obtained by multiplying the HH's exemption for financial and other assets by a factor of 20)
Bruckmeier & Wiemers (2012)	2005-2007	- Total HH's wealth is calculated as the sum of the individual assets
Harnisch (2019)	2005-2014	Different wealth specifications - Underlying assets are deduced from these incomes by assuming an annual interest rate of 3%
Fuchs et al. (2020) Austria	Data 2010 & 2016 (income info for 2009 & 2015)	To deal with wealth unavailability in the EU-SILC: A proxy for wealth is used: – HHs are regarded as ineligible if their incomes from interests, dividends, capital investments, and the property > the stipulated thresholds in the federal states

A.2 Detailed regressions

Table A.8: Marginal effects of non-take-up decision (temporary non-take-up at means)

	(1) unweighted probit	(2) weighted probit	(3) unweighted IV probit	(4) weighted IV probit
Panel A				
Simulated UBII benefit monthly amount (in euros)	-0.000245***	-0.000438***	-0.000210*	-0.000317
	(0.0000493)	(0.000112)	(0.0000955)	(0.000182)
Age	-0.0206	-0.0603*	-0.0453**	-0.0725**
	(0.0128)	(0.0254)	(0.0148)	(0.0268)
Age2	0.000159	0.000453	0.000422*	0.000590
	(0.000156)	(0.000314)	(0.000177)	(0.000330)
Married	0.361***	0.784***	0.346***	0.761***
	(0.0598)	(0.107)	(0.0732)	(0.117)
Primary education (ref. upper secondary)	-0.0592	0.00502	-0.0523	-0.000793
	(0.0603)	(0.126)	(0.0685)	(0.131)
Lower secondary education	-0.0694	0.103	-0.0566	0.108
	(0.0582)	(0.109)	(0.0631)	(0.111)
Post-secondary non-tertiary	0.213*	0.521***	0.262**	0.528***
	(0.0916)	(0.157)	(0.0969)	(0.158)
Short-cycle non-tertiary	0.640	0.363	0.688	0.370
	(0.370)	(0.358)	(0.366)	(0.352)
Bachelor or equivalent	-0.00659	0.509***	0.0606	0.533***
	(0.0680)	(0.151)	(0.0745)	(0.154)
Masters or equivalent	0.471**	0.424*	0.464**	0.432*
	(0.155)	(0.207)	(0.156)	(0.211)

Doctoral or equivalent	0.0692	1.363**	0.325	1.517**
	(0.257)	(0.473)	(0.291)	(0.496)
Migration status EU-national (Ref. Germans)	0.272**	0.258	0.258**	0.255
	(0.0875)	(0.133)	(0.0880)	(0.133)
Non-EU national	-0.389***	-0.142	-0.313***	-0.0984
	(0.0565)	(0.0997)	(0.0603)	(0.103)
Regular part-time	-0.585***	-0.540**	-0.598***	-0.546**
	(0.0993)	(0.175)	(0.106)	(0.179)
Vocational training	-1.021*	-0.0509	-1.088*	-0.134
	(0.503)	(0.575)	(0.549)	(0.587)
Marginal irregular part-time	-1.124***	-1.220***	-1.121***	-1.261***
	(0.105)	(0.181)	(0.116)	(0.193)
Not employed	-1.455***	-1.467***	-1.452***	-1.509***
	(0.0911)	(0.168)	(0.107)	(0.184)
Sheltered workshop	0.427	0.316	0.422	0.305
	(0.402)	(0.439)	(0.406)	(0.447)
Homeowner	0.792***	0.595*	0.769***	0.622*
	(0.185)	(0.247)	(0.188)	(0.251)
Single parent	-0.269***	-0.360**	-0.362***	-0.365**
	(0.0751)	(0.134)	(0.0796)	(0.136)
Disabled HH-H	0.259	0.268	0.260	0.252
	(0.156)	(0.207)	(0.155)	(0.209)
Female	0.263***	0.409***	0.346***	0.411***
	(0.0450)	(0.0877)	(0.0506)	(0.0895)
Eastern Germany	-0.392***	-0.315**	-0.395***	-0.300**
	(0.0551)	(0.106)	(0.0588)	(0.108)
Region: Rural (Ref. Intermediate)	0.0136	0.0544	-0.0511	0.0614

	(0.0528)	(0.106)	(0.0595)	(0.109)
Metropolitan	-0.0836	0.0353	-0.125*	0.0295
	(0.0474)	(0.0950)	(0.0524)	(0.0971)
With children	-0.211**	-0.166	-0.253***	-0.187
	(0.0645)	(0.116)	(0.0707)	(0.122)
Panel B				
First Stage Regression				
Dep. Var.: Sim. monthly benefit (UBII)				
Monthly private transfers			-0.711***	-0.922***
			(0.0393)	(0.0719)
Basic monthly subsistence level on household level			0.604***	0.613***
			(0.0211)	(0.0389)
First-stage F-stat. (Kleibergen-Paap Wald statistic)			512.58	153.926
N	5400	5400	4239	4239

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.3 Controls

A.3.1 Summary of Control variables used in the regression

The analysis incorporates covariates inspired by prior research, such as household composition metrics, which include the presence of children and single-parent households, as these factors influence the likelihood of benefit uptake. Characteristics of the household head, including age, gender, and migration background, are also included. Proxies for the anticipated duration of need, like having children, living in eastern Germany, or having a disabled household head, are used since they amplify the level of need and potentially increase benefit claims. Consistent with existing literature, the simulated benefit amount serves as a utility proxy in the analysis. This approach aligns with studies suggesting that welfare entitlements positively influence claims decisions. Furthermore, the migration variable is central to the study. Although descriptive statistics indicate differences in non-take-up rates (NTRs) between migrant and native groups, past research found no significant differences in the probability of claiming benefits across these groups. This analysis uses a similar migrant definition (based on citizenship) and examines this further in the regression results. Finally, the study addresses limitations in survey data by including proxies for stigma and information availability. A rural dummy variable is used to account for stigma costs, and municipality size serves as a proxy for awareness of basic income benefits.

Table A.9: Comparing pooled probit models, both weighted and unweighted: without vs. with controls, non-IV models

Model	Unweighted Probit	Unweighted Probit	Weighted Probit	Weighted Probit
Simulated UBII monthly benefit amount (in euros)	-0.000568***	-0.000245***	-0.000588***	-0.000438***
	(0.0000401)	(0.0000493)	(0.0000901)	(0.000112)
Controls	**x**	✓	**x**	✓
r2_p	0.0450	0.181	0.0287	0.249
N	5400	5400	5400	5400

Notes: Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.4 Further robustness checks

A.4.1 IV, additional instrument

Table A.10: Marginal effects of non-take-up decision (temporary non-take-up at means, using three conventional instrumental variables, pooled regression results of 2018 and 2017)

	(1) probit unweighted	(2) probit weighted	(3) IV probit unweighted	(4) IV probit weighted
Panel A				
Simulated UBII monthly benefit amount (in euros)	-0.000245***	-0.000438***	-0.000215*	-0.000356
	(0.0000493)	(0.000112)	(0.0000956)	(0.000185)
EU-national (Ref. Germans)	0.272**	0.258	0.258**	0.256
	(0.0875)	(0.133)	(0.0880)	(0.133)
Non-EU national	-0.389***	-0.142	-0.313***	-0.0965
	(0.0565)	(0.0997)	(0.0603)	(0.103)
Panel B				
Dep. var.: simulated UBII monthly benefit				
Monthly private transfers			-0.706***	-0.898***
			(0.0394)	(0.0737)
Monthly social security pensions			-0.250*	-0.420*
			(0.125)	(0.182)
Basic monthly subsistence level on household level			0.604***	0.613***
			(0.0211)	(0.0388)
First-stage F-stat.(Kleibergen-Paap Wald statistic)			342.35	104.702
F(3,4210)			(p-value 0.0000)	(p-value 0.0000)
N	5400	5400	4239	4239

Standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

A.4.2 Flat changes

Table A.11: Table of sensitivity checks

	2018				2017		
Model	**a**	**b**	**c**	**d**	**a**	**b**	**c**
Wealth	No	(Yes)	(Yes incl. vehicles)	(Yes incl. vehicles)	No	(Yes)	(Yes incl. vehicles[1])
Housing costs	No cap	No cap	No cap	Imputed for INR	No cap	No cap	No cap
NTR	**52.06**	**43.09**	**42.01**	**42.25**	**50.35**	**40.42**	**38.62**
NTR[2]	**46.26**	**36.45**	**35.16**	**35.48**	**43.87**	**33.12**	**31.24**
	Needs			**Income**		**Housing**	
Δ	$\uparrow$ **+5%**	$\downarrow$ −5%		$\uparrow$ **+5%**	$\downarrow$ −5%	$\uparrow$ **+5%**	$\downarrow$ −5%
NTR	**43.32**	**41.16**		**41.01**	**43.75**	**42.4**	**41.92**
Δ	$\uparrow$ **+10%**	$\downarrow$ −10%		$\uparrow$ **+10%**	$\downarrow$ −10%	$\uparrow$ **+10%**	$\downarrow$ −10%
NTR	**44.99**	**39.81**		**39.5**	**45.6**	**42.94**	**42.04**

Notes: All specifications listed here are based on the month of the interview and refer to the core family or household (HH). The sensitivity checks in the second part of this table are based on model (c) specification. It should be noted that 2018 and 2017 (i.e., specifications a & b) are quite comparable. The only difference is that for 2017, there is no data in the SOEP on private pension contributions to Riester Insurance or Rürup. INR refers to (Item Non-Response) where rent is imputed for all missings and non-homeowners.

1 The model's predictions for the receipt indicator and the predicted simulated amounts yield a high correlation with the SOEP observed indicators (correlation: 71.6%, 67%, respectively) for this given year and this particular specification

2 The denominator includes beta-errors.

Table A.12: Descriptive statistics of unweighted and weighted IV regressions

	unweighted IV		weighted IV	
Variable	Mean	Std. dev.	Mean	Std. dev.
Non-takeup	0.3111583	0.463022	0.3954633	0.4890076
Age	39.30125	11.61371	43.0526	12.64933
Age2	1679.435	957.8153	2013.494	1093.459
Married	0.4170795	0.4931344	0.2280419	0.4196193
Education				
Primary education	0.252418	0.434451	0.1195764	0.3245038
Lower secondary education	0.215381	0.4111349	0.237581	0.4256512
Post-secondary non-tertiary	0.0542581	0.226553	0.0808994	0.2727127
Short-cycle non-tertiary	0.0028309	0.0531367	0.0049302	0.07005
Bachelor or equivalent	0.1304553	0.3368434	0.0808158	0.2725842
Masters or equivalent	0.0169851	0.1292307	0.0277897	0.1643892
Doctoral or equivalent	0.0054258	0.0734686	0.0023709	0.0486403
Migration status EU-national				
GER	0.3899505	0.4877963	0.7171499	0.4504373
EU	0.0669969	0.2500462	0.0741182	0.2619941
Non-EU	0.5430526	0.4982018	0.2087318	0.4064503
Employment status				
Full-Time..	0.0636943	0.2442363	0.0775818	0.267544
Regular part-time	0.1309271	0.3373604	0.1836489	0.3872433
Vocational training	0.0011795	0.034328	0.0016788	0.040943
Marginal irregular part-time	0.1023826	0.3031866	0.1171821	0.3216751
Not employed	0.6970984	0.4595672	0.5980304	0.4903537
Sheltered workshop	0.0047181	0.0685342	0.0218779	0.1463023
Homeowner				
0	0.9893843	0.1024963	0.9814269	0.1350274
1	0.0106157	0.1024963	0.0185731	0.1350274
Single parent				
0	0.8247228	0.3802489	0.8540147	0.3531331
1	0.1752772	0.3802489	0.1459853	0.3531331
Disabled HH-H				
0	0.977825	0.1472699	0.9541216	0.209246
1	0.022175	0.1472699	0.0458784	0.209246
Female				
0	0.4994102	0.5000586	0.4607729	0.4985177
1	0.5005898	0.5000586	0.5392271	0.4985177
Eastern Germany				
0	0.7761264	0.4168875	0.7614979	0.4262179
1	0.2238736	0.4168875	0.2385021	0.4262179
City size				
Rural	0.2547771	0.4357872	0.243692	0.4293597
Metropolitan	0.4324133	0.4954694	0.4698525	0.4991492
With children				
0	0.2469922	0.431313	0.363792	0.4811466
1	0.7530078	0.431313	0.636208	0.4811466
Simulated monthly benefit (EUR)	994.5719	546.0048	759.2077	434.5596
Monthly private transfers (EUR)	28.4525	105.4489	20.35382	79.98642
Monthly subsistence (EUR)	1058.011	592.0369	761.4293	461.2863

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