Analysis Report

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Presidente: *Sebastiano Fadda*
Direttore generale: *Santo Darko Grillo*

Riferimenti
Corso d'Italia, 33
00198 Roma
Tel. +39 06854471
www.inapp.org

MOSPI – MODERNIZING SOCIAL PROTECTION SYSTEMS IN ITALY
VS/2018/0414

ANALYSIS REPORT

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Authors
Michele Bavaro, Stefano Boscolo, Riccardo Conti, Elena Fabrizi, Chiara Puccioni

Report completed on September 2021

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Introduction

The Analysis Report represents the latest milestone of the MOSPI project and follows the release of the "T-DYMM 3.0 Forecast Model Report", dated March 2020. The latter described the progress made in terms of data sources (updated and expanded), in the econometric specifications and with the introduction of innovative modules. This report benefits from the observations received in the Peer Review seminar held in March 2021, during which most of the advancements hereby illustrated were preliminarily presented.

Chapter 1 provides summary information on the latest updates on how the database for T-DYMM 3-0 was constructed. We also list the main alignment assumptions and their sources. Chapter 2 concentrates on the module structure of T-DYMM 3.0 and on the econometric analysis underpinning the key processes. Chapter 3 contains the core content of this report, the results of the Baseline scenario for the period 2020-2070, and it prepares the ground for the final delivery of the MOSPI project, where we will present results from alternative policy scenarios.

1. Data

In this chapter, we briefly sum up the characteristics of the data used for the simulations and the latest updates to what was described in the latest intermediate MOSPI report (MEF *et al.* 2020).

1.1 Microeconomic data

The core of T-DYMM's dataset was compiled by linking the survey data of the European Union Statistics on Income and Living Conditions (EU-SILC), delivered for Italy by the Italian National Institute of Statistics (ISTAT), with the administrative data from the Italian National Institute of Social Security (INPS). The merging procedure was conducted through individual tax codes (*codici fiscali*) that are subsequently anonymized. We call the merged dataset AD-SILC.

AD-SILC is an unbalanced panel dataset that in its current version comprises the information contained in all SILC waves from 2004 to 2017 and in the INPS archives (for the linked individuals). From SILC, we derive longitudinal data on socio-economic characteristics (up to 4 years) for a total of 254,212 individuals; from INPS, we derive longitudinal data on pensions (disability, old-age, survivor) and working history (occupational status, income evolution, contribution accrual), for a total of 6,182,926 observations over the 1922-2018 period.

The main innovations of the current version of AD-SILC (so-called AD-SILC 3.0) compared to its predecessors are:

i. The addition of 5 SILC waves (2013-2017, a 25% increase in the sample size compared to AD-SILC 2.0);
ii. The merge of information from Tax returns and Cadastre (collected by the Finance Department of the Italian Ministry of Economy and Finance) for the corresponding 2010, 2012, 2014 and 2016 SILC waves;
iii. The inclusion, by means of a statistical matching procedure, of information from the Survey on Household Income and Wealth (SHIW) conducted by the Bank of Italy.

These last two innovations in the data sources make it possible to build a complete dataset on household wealth that constitutes one of the crucial additions to the present release of T-DYMM. House wealth is constructed based on the administrative data from Cadastre and Tax returns, whereas from SHIW we retrieve information on financial wealth and liabilities. We follow a specific correction procedure for data on financial wealth to take into account a well-documented under-reporting issue in SHIW (see Appendix 2 for a complete explanation).

Cooperation has been established between the Treasury Department (owner of T-DYMM) and the Finance Department (owner of the data from Tax Returns and the Cadastre), so that in the future a stronger linkage between datasets may be explored. A first contact was established with the Italian Ministry of the Interior to assess the feasibility of linking AD-SILC 3.0 with Register data (*Anagrafe Italiani Residenti all'Estero*, AIRE and *Anagrafe Nazionale della Popolazione Residente*, ANPR) to gain additional information on the emigration phenomenon and furtherly expand the Migration Module. The possibility of extending a statistical matching procedure to merge AD-SILC 3.0 with survey data from INAPP (PLUS and/or RIL), a possibility mentioned in the latest intermediate report, has been discarded at this stage. PLUS and RIL may still be employed for *ad hoc* analysis on specific sub-groups of the labour force that are not specified in AD-SILC 3.0.

AD-SILC 3.0 is used: i) to analyse historical dynamics (e.g., within the labour market); ii) to estimate transition probabilities and determinants of labour income to be included in T-DYMM (these estimates are carried out over a panel version of AD-SILC); iii) to derive the starting sample for the simulations (these run on a single extract of AD-SILC, relative to the 2016 EU-SILC wave, linked with all the aforementioned data).

Before running the simulations, the starting sample needs to be properly calibrated in order to improve the overall representativeness of the series of dimensions we are interested in[1]. We perform integrative calibration following Lemaître and Dufour (1987)'s methodology by applying Deville and Särndal (1992)'s generalized raking procedure. Subsequent to the weight calibration, we expand the starting sample by multiplying individuals by calibrated weights, which is necessary to overcome issues of representativeness that emerge when making use of alignment methods in dynamic microsimulation (Dekkers and Cumpston 2012). We then draw with replacement 100 samples of 200,000 households and select the best-fitting sample with respect to administrative data. As a result, the starting sample is made up of 476,944 individuals.

1 We calibrate for all dimensions used in the 2016 IT-SILC weights and other dimensions, such as: the distribution of non-national population by sex, area of birth and educational level; the distribution of the population by number of family members; the number of recipients of specific income sources (e.g., rental income; self-employment income subject to substitute tax regimes; and others); the distribution of recipients of gross income subject to PIT by income groups; and so on.

1.2 Exogenous data and alignments

Exogenous data are used to align a number of patterns within the simulations. Alignment is a technique widely used in (dynamic) microsimulation modelling to ensure that the simulated totals conform to some exogenously specified targets or aggregate projections (Baekgaard 2002; Klevmarken 2002; Li and O'Donoghue 2014). It is a way of incorporating additional information that is not available in the estimation data: the underlying assumption is that the microsimulation model is a poor(er) model of the aggregate, but a good model of individual heterogeneity. More simply, institutional models such as T-DYMM may wish to make sure that certain demographic or macroeconomic dynamics stay in line with institutional projections and focus on individual/household distributions. Alignments may be easily modified to simulate sensitivity scenarios.

The main sources for alignments in T-DYMM are:

- Eurostat demographic projections[2], used to align mortality rate, fertility rate, immigration and emigration by age and gender;
- Ageing Report[3] assumptions, used to align employment rate, inflation growth, GDP growth, productivity growth, disability rate by age and gender, returns on risk-free assets;
- Population-level data by the Italian Finance Department, used to align the number of households paying rents and the total beneficiaries of specific tax expenditures and substitute regimes;
- Data by ISTAT, used to align the probability of leaving the household of origin, the age and country of birth of migrants, education levels, acquisitions of houses, the propensity to consume, the propensity to marry and to divorce;
- Population-level data by INPS, used to align the occurrence of disability allowances and inability pensions;
- Population-level data by COVIP (Italian Vigilance Committee on Private Pension Plans), used to align enrolment rates to private pension plans.

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2 For the current version of T-DYMM, Europop 2019 projections are utilized.

3 For the current version of T-DYMM, assumptions underlying the 2021 Ageing Report from the Ageing Working Group of the Economic Policy Committee are utilized (European Commission 2021).

Appendix 1: Adjustment for self-employed workers – INPS and Tax Returns data

As previously mentioned, the AD-SILC dataset is used both to estimate transitions in the labour market and to derive employment and self-employment income levels. INPS archives gather information related to individual working histories, but reported income differs in most cases from declared labour income in Tax returns data. Reported income for employees and atypical workers is gross of social insurance contributions (hereinafter SICs) paid by the worker, while income collected in tax returns data is net of any contributions. As for self-employed individuals, we observe that reported earnings in INPS archives are in line with declared earnings except for specific categories of the self-employed – i.e., individuals with declared earnings below statutory thresholds set for the payment of SICs[4]. In the Italian tax system, low-earning self-employed workers are required to pay a fixed amount of SICs regardless of the amount of earnings declared for tax purposes (e.g., the contributory rate for craftsmen and traders aged over 21 in 2021 amounts to 24%, which multiplies a threshold y=15.953 (n/12), with n equal to the number of months worked, if declared earnings are below y). This means that, for a series of observations in the AD-SILC dataset, reported income for contributory purposes is systematically greater than declared income for tax purposes.

Bearing in mind what has been said above, it is easy to understand that the use of earnings from INPS archives for the estimate of self-employed worker's labour income leads to an underestimation of the true poverty conditions among these workers and it is likely to inflate poverty thresholds calculated for the overall population.

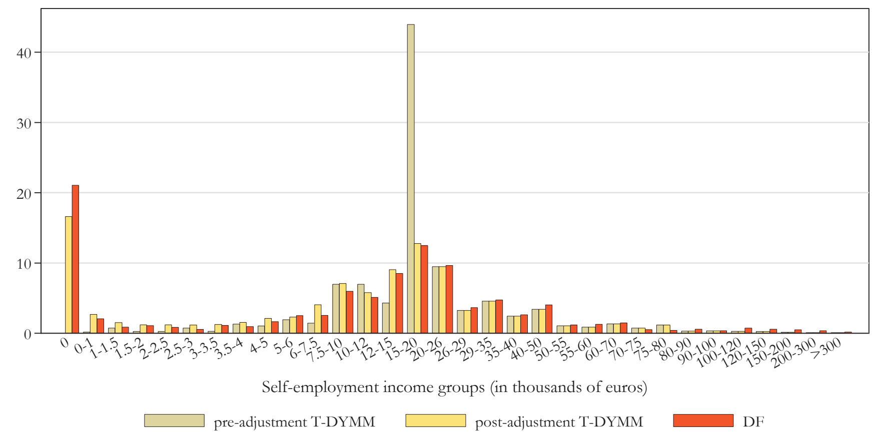
To tackle this issue, we have imputed the ratio between earnings as declared for tax purposes and earnings as collected in INPS archives (hereinafter indicated with θ) for self-employed workers with reported earnings for contributory purposes exactly equal to observed statutory thresholds in the AD-SILC dataset. The imputation is performed by using propensity score matching analysis taking the Mahalanobis distance measure. Given that θ is known for a set of observations in the AD-SILC dataset – i.e., those observations for whom we observe labour income as declared for tax purposes, that is the 2009, 2011, 2013 and 2015 tax years – we split the AD-SILC dataset in two groups: the donor sub-sample, which gathers observations eligible to act as donors in the imputation of θ; and the treated sub-sample, which is made of observations for whom we do not have tax returns data and therefore θ is missing. Subsequent to

[4] Taxable income for self-employed workers is calculated by subtracting social insurance contributions from earnings, and that is why we find no relevant differences in income levels between INPS and tax returns data for those individuals with earnings equal to or higher than average declared earnings.

the imputation, we obtain self-employment income by multiplying reported income as collected in INPS archives by θ.

Figure 1.1 presents the percentage distribution of self-employed workers before and after the imputation of θ by self-employment income groups. The pre- and post-adjustment AD-SILC distributions are compared with the distribution of self-employed workers from administrative data (DF). First, it should be noted that pre-adjustment values are highly concentrated in the interval € 15,000-20,000. This reflects the high frequency of self-employed individuals working the whole year among those with reported income for contributory purposes equal to observed statutory thresholds. Second, in line with the theoretical framework underpinning the analysis, we do not observe individuals with pre-adjustment values falling into the first income group (i.e., self-employed with negative or zero earnings). Overall, the post-adjustment distribution fits the reference distribution rather accurately, keeping in mind that the imputation exercise affects self-employed workers with earnings included in the interval € 0-20,000.

Figure 1.1 Distribution of self-employed workers by self-employment income groups



Note: percentages are not weighted and income values refer to price levels in 2015. DF stands for tax return micro data for the 2015 tax period. Pre- and post-adjustment T-DYMM are obtained from the AD-SILC dataset in the interval 2004-2017.

Source: T-DYMM 3.0 – Authors' elaborations on AD-SILC 2004-2017

Appendix 2: Correction for the under-reporting of financial wealth in SHIW

Italian data on household wealth are not particularly rich, especially if we focus on financial wealth. One of the main sources of information is the SHIW survey, held by the Bank of Italy. However, as well known in the literature (Bonci *et al.* 2005), there is an under-reporting issue in the micro data since they do not match with the amounts reported in the Italian National Accounts (NA). In 2016, the total amount of financial wealth in Italy was 690 billion according to SHIW (a value obtained weighting the sample values with the weights associated with each household), whereas 3,278 billion according to the National Accounts (excluding the insurance reserves and standard guarantees). In other words, the financial wealth reported in SHIW accounts for about 21% of the total Italian household financial wealth. In terms of total net wealth (real wealth + financial wealth – liabilities), SHIW accounts for about 53% of the NA value. For T-DYMM 3.0, we decided to undertake a procedure of correction in the initial values of financial wealth in order to reduce the relevance of this issue especially in the starting years of the simulation. In this Appendix, we describe the adopted procedure and show some evidence. Even though the procedure has been applied to all the recent SHIW waves in order to improve the estimates used in the simulation, we select the 2016 wave since it is the one adopted in the statistical matching to attribute financial wealth to the starting sample. The same procedure has been applied to wealth and liabilities.

The correction procedure foresees three steps, as in Boscolo (2019):

1. Correction for ownership, following Brandolini *et al.* (2009);
2. Attribution of financial wealth to households who are "new" owners;
3. Correction for the amount of financial wealth owned, following D'Aurizio *et al.* (2006).

In the first step, we proceed to study the probability of owning the specific financial instruments that are part of financial wealth (liquidity, government bonds, corporate bonds, stocks, mutual funds, insurance). We run a multinomial model to determine the probability of owning a more or less sophisticated investment portfolio. Then, we use logistic models to analyse the impact of socio-economic and financial variables on the probability of owning a specific instrument.

In the second step, we impute through matching (with Mahalanobis distance measure) the value of financial activities for households to which possession of one of the financial instruments was associated.

Finally, we use the ratios between "true" and declared values found in SHIW 2002 by D'Aurizio *et al.* (2006) to adjust the levels of financial activities. We run regressions with households' demographic and socio-economic characteristics as explanatory variables for each of the instruments to attribute a new value of financial wealth in

the more recent waves that we use for the estimates and for the starting sample of the simulations.
The total amount of financial wealth in 2016 after the correction amounts to 2,494 billion. The applied procedure significantly reduces the gap between the SHIW totals and the NA, as the "corrected" total of financial wealth accounts for 76% of the NA[5]; in the case of net wealth, the percentage decreases to 73%.
Regarding the adjustment in the household ownership of financial wealth, the main result is that the number of households owning financial wealth increases from 6,183 (83% of the SHIW sample) to 6,920 (93%). Moreover, as shown in Table 1.1, one relevant change involves the number of financial instruments owned[6], which increases significantly. Finally, another major difference is found in the household distribution of financial wealth. The correction procedure results in a significant change in the Gini index, which equals 0.762 before the correction and becomes 0.852 afterwards.

Table 1.1 Number of financial instruments owned

Number of financial instruments	Before adjustment		After adjustment	
0	6108	82.32	5598	75.44
1	989	13.33	580	7.82
2	270	3.64	445	6.00
3	53	0.71	797	10.74
Totale	**7420**	**100.00**	**7420**	**100.00**

Source: Authors' elaborations based on SHIW 2016

5 In the paper by D'Aurizio *et al.* (2006) the correction made it possible to obtain about 85% of the NA totals.
6 In this case, we consider only three financial activities coherently with the model: government bonds, corporate bonds and stocks.

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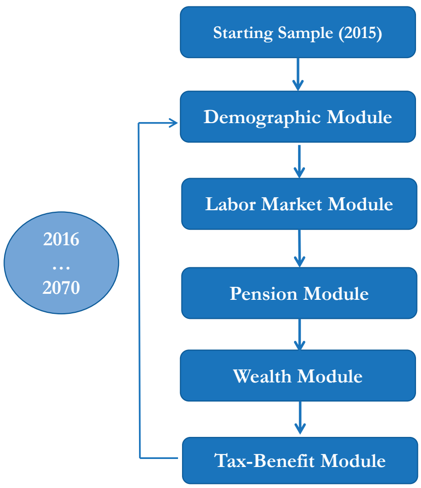
2. Model structure, processes, and estimates

The present section illustrates the current structure of the baseline version of T-DYMM (so-called T-DYMM 3.0) and some of the estimations conducted on AD-SILC 3.0 and SHIW that are at the foundation of the model. Building on the analyses presented in MEF *et al.* (2020), we shall illustrate what underlies the results presented in Chapter 3. The model is organized in five modules, as shown in Figure 2.1, and operates sequentially[1]. The starting sample is set in 2015 and simulations run on an annual basis from 2016 until 2070 (the projection horizon of the 2021 Ageing Report by the European Commission).

Figure 2.1 Module structure of T-DYMM 3.0



[1] The organization in modules is logical and does not strictly represent the sequence of processes that the model solves. For instance, the "consumption/saving" process, which by logic belongs to the Wealth Module, is solved last, as one can only compute consumption on the basis of a final definition of income (net of taxes and comprehensive of social assistance).

2.1 Demographic Module

Within the Demographic Module, the sample evolves in its components inherent to demographic aspects. Individuals in the sample are born, age, die, migrate, get educated, leave their household of origin, form couples and separate and become disabled. We shall briefly describe these processes.

2.1.1 Ageing and mortality

T-DYMM is an annual model. All statuses are updated annually, starting from ageing. Mortality rates are aligned by gender and age to the latest Europop projections, included in the 2021 Ageing Report assumptions. We are currently considering the possibility of integrating an estimation of heterogeneity in mortality, i.e. distributing average mortality rates (by age and gender) across income and wealth classes, educational levels, civil status, etc.

2.1.2 Births

Fertility rates (for women between 14 and 50, by age) are aligned to the latest Europop projections. Parameters estimated via logit regressions in AD-SILC 3.0 distribute the probability of having children across women by civil status, duration of marriage/cohabitation, presence of other children and employment status.

2.1.3 International migration

Considering the well-known scarcity of quality data on the international migration phenomenon, we have opted for a rather simplified modelization of the Migration Module in T-DYMM 3.0, which could serve as a basis for future expansions when more microdata become available.

We focus on three essential dimensions to define migrants: age, gender and area of birth (Italy, EU and non-EU)[2]. We simulate immigration and emigration separately and follow Dekkers (2015) and Chénard (2000) in implementing a "cloning procedure" for households using Chénard's Pageant algorithm, which makes it possible to select households in the model (to either immigrate or emigrate) while ensuring that certain individual characteristics (age, gender and area of birth) are matched.

Inflows and outflows of migrants are aligned to Europop projections; education (for immigrants) and area of birth (for both immigrants and emigrants) is assumed constant (by gender and age group) according to respectively OECD[3] and ISTAT data.

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2 Conscious of the debate on the topic in our work we have opted to identify immigrants by area of birth, not citizenship, as already expressed in MEF *et al.* (2020).

3 Database on Immigrants in OECD Countries (2015-2016), see: www.oecd.org/els/mig/dioc.htm.

Immigrants are derived from clones of the incumbent sample, but lose all dimensions of the originals other than age and gender (which are aligned) and household compositions; the implicit assumption is that all immigrants "start fresh" upon their arrival in Italy, carrying no relevant work experience with them and no pension rights. These simplifying assumptions are necessary due to lack of data, though they may not be too stringent, given the age structure of the immigrant population and the segregation within the labour market.

As no data is available at this point to model emigrants' behaviour once they leave Italy, they are simply deleted from the simulation, i.e., households (and individuals) are not followed in their (possibly) multiple entries/exits. Therefore, while we align macro numbers to Europop projections, we may be overestimating the incidence of the migration phenomenon on a micro basis.

2.1.4 Disability

Each year T-DYMM assigns an individual probability of becoming disabled ("strongly-limited in daily activities on a long-term basis", according to the EU-SILC definition), based on regression parameters estimated on AD-SILC that highlight the role of education, income quintile and the disability state at time t-1 (disability is highly persistent). Average probabilities by gender and age class (nineteen age classes) are aligned to the Reference scenario of the 2021 Ageing Report[4].

2.1.5 Education

Individuals in the model may hold i) elementary, ii) lower-secondary, iii) upper-secondary or iv) tertiary education. Following the legislation on compulsory education in Italy, in simulation years T-DYMM assigns lower-secondary as the lowest educational achievement. Probabilities of obtaining tertiary educational degrees are assigned individually based on estimations run on the AD-SILC dataset. Due to the limited availability of data concerning the moment in time when the latest educational level was achieved, the only explanatory variables employed are parental educational achievements. Lower levels of education are assigned randomly, while all average probabilities are aligned by gender to ISTAT data[5]. Individuals receive lower-secondary education at 16, upper-secondary (if entitled) at 19 and tertiary (if entitled) randomly between 21 and 29 years of age[6].

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4 The Reference Scenario incorporates 50% of the increase in life expectancy to correct the probability of falling disabled, i.e. increases in life expectancy produce a corresponding 50% increase in the time span spent in good health (European Commission 2021).

5 From 2020 onward, probabilities are kept constant to the values of 2019 for individuals aged 30-34.

6 We follow the latest data published by Almalaurea to attribute age-specific average probabilities of exit from the tertiary education system (Almalaurea 2020).

2.1.6 Leaving household of origin

Because T-DYMM has the ambition of estimating poverty and redistribution dynamics, income variables will have to be estimated at the household level. Therefore, it is crucial for households to be properly designed. Each year, young individuals still living with their parents are assigned a random probability of leaving and forming a new household[7]; the latest ISTAT data on the quota of young people living with their parents are used to align future exit flows.

2.1.7 Coupling/marriage and separation/divorce

Each year single individuals are assigned a probability of forming a couple according to individual probabilities estimated on AD-SILC[8]. The overall propensity to form couples is aligned to ISTAT data. Since the past few years have seen a visible and somewhat uncharacteristic decrease in the propensity to marry, we assume that the number of marriages every 1,000 individuals will start rising again in 2020 and go from 0.3% in 2019 to 0.4% in 2029 (corresponding to its 2008 value). On top of that, following the variation in census data, we assume that for every four marriages, a new informal cohabitation is established. Once individuals to be coupled are selected, they are matched according to a score that takes into account age, education differentials and a dummy returning 1 if both potential partners are employed (we are attempting to reproduce the assortative mating behaviour that we observe in the AD-SILC sample). Each year, couples are assigned a probability of divorcing/separating[9] according to individual probabilities estimated on AD-SILC[10]. The overall propensity to divorce/separate is aligned to ISTAT data. The passing of the legislation on the so-called "fast divorce" (*divorzio breve*, which has sped up divorce procedures) produced a break in the series in 2015-2016, when the number of yearly divorces doubled compared to previous years. In order to account for that and for the following gradual reduction of yearly occurrences in the 2017-2019 period, we assume that the propensity to divorce/separate will keep reducing linearly and, 10 years after the approval of the aforementioned legislation, stabilise at a rate equal to the average of the pre-2015 and 2015-2016 value.

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7 In order to avoid unrealistic developments, if they are single, individuals are allowed to leave their household of origin only if they meet a certain income threshold.

8 Covariates include age category, working status in *t-1* and a dummy for individuals who have just left their original household, who are more likely to form a family right away.

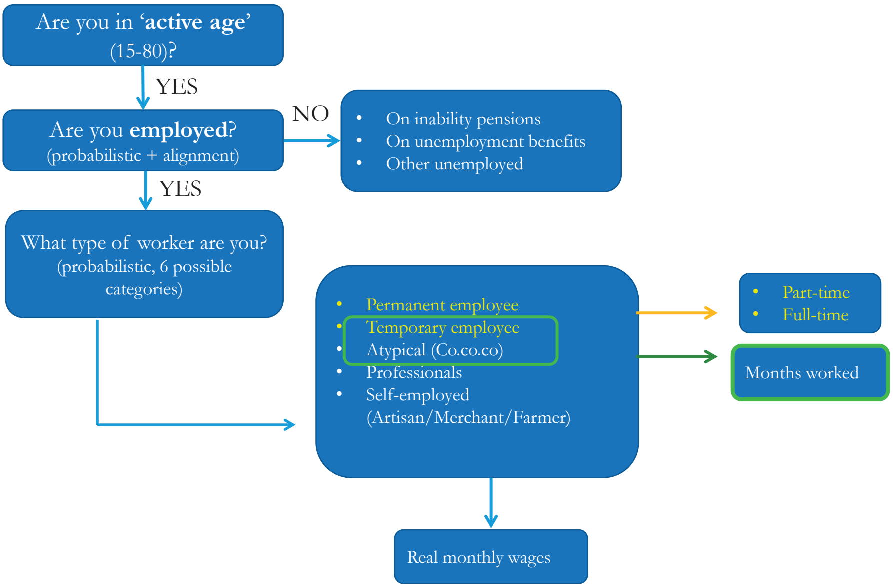
9 In the absence of specific data, we assume that informal marriages follow the same trajectory as formal marriages.

10 Covariates include age category, duration of marriage and presence of children under 6 years of age.

2.2 Labour Market Module

The Labour Market module mainly simulates the individual transitions between different employment statuses and, once a labour market status is assigned, imputes the corresponding level of income. This module is based on a sequence of nested choices, as shown in Figure 2.2, occurring by a series of logistic or multinomial logistic behavioural equations, which serve to model employment decisions and job characteristics.

Figure 2.2 Structure of the Labour Market Module



The first process simulated concerns the probability of being employed for those between 15 and 80 years of age. Then, for those working, the probabilities of different contractual arrangements are estimated through a multinomial logit. For employees, a further logit regression determines who works in the public[11] or private sector and who works part-time or full-time. Furthermore, we estimate the probability of working all year and for those employed only some months, we estimate the number of months worked. Additionally, real monthly wages are estimated for each of the different em-

[11] Shares of both fixed-term and open-ended public employees are aligned to the corresponding shares in the population of 2015.

ployment categories identified[12]. Finally, the very last step is the simulation of yearly labour gross incomes, indexed to labour productivity and consumer price index.
With respect to earlier versions of T-DYMM, we have improved the structure of the module mainly by replacing the binomial structure with a multinomial when modelling occupational status choices and by allowing students and retirees to work, as planned in MEF *et al.* (2020). Because of their specificity, working pensioners follow a separate (simplified) process from the rest of the workers. Individuals receiving inability pensions or disability allowances that are not compatible with labour income are excluded from the sample of potential workers. As an additional innovation, whenever relevant we have included fatherhood dummies[13] among the possible explanatory variables, to capture parenthood effects on labour market outcomes for males.
Generally speaking, to predict the different labour market outcomes, regressors are selected among the demographic, socio-economic individual or household characteristics and individual working career features. However, among all the variables included in the AD-SILC dataset, we use only those for which we can project the evolution over the simulation period, to keep the same degree of heterogeneity accounted for in both the regressions and the microsimulation model. When the sample size is large enough, separate regressions are fitted for males and females. If not differently specified, all models are estimated through pooled OLS estimators[14], either because we test that the fraction of variance due to individual effects is close to nil, or in order to guarantee a coherent amount of individual heterogeneity both in the regressions and in the model[15] (Shmueli 2010; Martini and Trivellato 1997), or because we are still evaluating more sophisticated techniques[16].
In what follows we provide a short description of the module's main processes and methodological implementation.

12 Open-ended and fixed-term contracts are grouped in public and private employees.
13 Namely, the presence of children aged between 0 and 6 years old, or between 0 and 3 and above 4 years old, included in the estimation of months worked and wages earned.
14 Note that because of the panel data nature of the dataset, each coefficient encompasses two sources of variation in X, within-subject variability and between-subject variability. Pooled OLS estimator simply treats within- and between-group variation as the same (i.e., it pools data across waves).
15 In some cases we cannot assign, in the microsimulation model, the individual heterogeneity that would be extrapolated from the regressors' effects if techniques for panel data model such as the Random Effects model were used.
16 In particular, as also suggested during the second international workshop on the Mospi project held on 24 March 2021, we are separately considering two specific improvements: the possibility of using dynamic models – which include the lagged dependent variable as a regressor – and of applying a correlated random effect estimator. The first enhancement is motivated by the fact that the labour supply behaviour measured at the individual level displays a great deal of persistence (e.g., Booth *et al.* 1999; Francesconi 2002). Still, the models already include covariates indicating the cumulated past work experience, which partially accommodate for this aspect. The second advancement aims at better exploiting the panel nature of the AD-SILC sample without incurring in some of the pitfalls associated with the random effect models.

2.2.1 In work

The first process is the one determining whether individuals are employed. Those not entering/staying in the labour market are assigned to an "out-of-work" status, which includes those assigned in other modules to inability pensions, unemployment benefits or other forms of unemployment or inactivity. We use the macroeconomic assumptions underlying the 2021 Ageing Report to align employment rates by gender and age. Table 2.1 reports the estimated parameters for the regression, modelling the probability of being employed by gender. For equal labour market characteristics, regardless of gender, individuals still studying, those retired and those disabled or receiving some INPS treatment related to disability as well as mothers of young children are less likely to be employed, in line with expectations and the relevant literature[17].

Instead, older, more educated and experienced individuals are more likely to work, together with immigrants born in extra-EU countries. This result is not surprising because those immigrants need a visa or a resident permit to remain in the country, often issued under proof of employment in the country. Marriage shows a premium for men and a disadvantage for women, in line with the literature[18], while some sort of assortative mating emerges when looking at the likelihood of being employed depending on the working status of the partner. Concerning characteristics related to the labour market, a higher overall working experience, even if not consecutive and regardless of category of employment, increases the likelihood of being employed in time *t*; vice versa for unemployment. Chances of being employed in time *t* increase in particular if employed as professional, self-employed or permanent employee in *t-1*.

[17] See in particular Bertrand (2020) for a review on gender inequality in the labour market.

[18] The fact that marriage may discourage female employment is a well-established result of the literature. Concerning men, the same mechanisms found by the literature to explain married men's wage premium may be at play here. For example, marriage makes men more productive because of gender imbalances in the household chores division; also, married men may hold specific characteristics, such as motivation or reliability, likely to affect both wages and employment probability (Bardasi and Taylor 2008).

Table 2.1 Probability of being employed

	Male		Female	
	inwork		inwork	
	b	se	b	se
Extra-EU born	0.264***	(0.041)	0.186***	(0.038)
Studying	-1.050***	(0.033)	-1.043***	(0.033)
Retired	-2.291***	(0.047)	-1.926***	(0.061)
Age	0.372***	(0.012)	0.070***	(0.005)
Age^2	-0.009***	(0.000)	-0.001***	(0.000)
Age^3	0.000***	(0.000)		
Upper sec. Degree	0.260***	(0.020)	0.399***	(0.021)
Tertiary degree	0.584***	(0.032)	0.855***	(0.031)
Disabled	-0.340***	(0.052)	-0.303***	(0.057)
Inability pension	-1.123***	(0.096)	-1.092***	(0.093)
Disability allowance	-0.982***	(0.120)	-0.870***	(0.126)
Invalidity pension	-1.241***	(0.088)	-1.358***	(0.145)
In couple	0.152***	(0.027)	-0.289***	(0.033)
Partner working (lag)	0.178***	(0.027)	0.138***	(0.030)
Experience	0.044***	(0.002)	0.045***	(0.002)
Duration in last spell if out-of-work	-0.193***	(0.007)	-0.190***	(0.006)
Duration in last spell if working	0.022***	(0.001)	0.021***	(0.002)
Open-ended private (lag)	3.530***	(0.032)	3.858***	(0.034)
Fixed-term private (lag)	2.830***	(0.037)	3.163***	(0.038)
Open-ended public (lag)	3.820***	(0.055)	4.723***	(0.060)
Fixed-term public (lag)	2.997***	(0.124)	3.675***	(0.083)
Professionals (lag)	4.681***	(0.110)	4.328***	(0.126)
Self-employed (lag)	4.110***	(0.051)	4.545***	(0.065)
Atypical (lag)	3.601***	(0.071)	3.194***	(0.068)
Children aged 0-6			-0.319***	(0.029)
Constant	-5.650***	(0.161)	-2.370***	(0.099)
ROC	0.723		0.738	
Pseudo-R^2	0.974		0.977	
Nr of obs	253370		250303	

Source: elaboration on AD-SILC data, coefficients in units of log odds. Omitted category in the dependent variable: permanent employees

2.2.2 Employment categories

Among those assigned to work, the module's next processes assign each to their respective employment category. In the model, workers are allowed to perform only one type of job per year[19]. Concerning the data on which we run estimations, for those who hold more than one job[20], we choose the predominant employment category in a year based on the following criteria, in order of importance: level of earnings, duration of the working relationship, level of social security contributions, latest job position held within the year, employment stability (e.g. open-ended contracts are more stable than fixed-term contracts).

Because working pensioners are mainly male, are less educated and have a much higher incidence of certain job types than non-retired workers, we fit separate models for working pensioners and the rest of the "in work" individuals. For those not retired, each working individual is assigned to one of five possible job types listed in Figure 2.1[21] by means of a multinomial logit. Instead, for those who are retired, the only relevant employment categories in AD-SILC data are the permanent employees in the private sector, the self-employed and those with atypical[22] contractual arrangements. Tables 2.2 and 2.3 report regression results for the non-retired, separated by sex. Coefficients should be interpreted as the effect of a variable increasing or decreasing the likelihood of working in a certain job type relative to the omitted one, i.e. permanent employees. Regardless of gender and keeping labour market characteristics a constant, among demographic characteristics only the status of foreigner always increases the likelihood of working as an open-ended employee in comparison with the other employment categories. Studying is more associated to temporary arrangements such as fixed-term and atypical and less with self-employed or professionals (only for male). As age (albeit at a decreasing rate) and education increase, individuals are less likely to be employed as permanent employees than anything else, exception made for fixed-term male employees (and a few other exceptions).

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19 We are currently working at relaxing this assumption, as holding multiple jobs at the same time is a significant characteristic to keep into account in defining employment, especially considering the evolution of the world of work.

20 About 10% of working individuals in AD-SILC data.

21 See MEF *et al.* (2020), chapter 2 for a detailed description of the Italian contractual arrangements covered in AD-SILC.

22 Workers who pay their social contributions to INPS in the section of "*Gestione Separata*" ("parasubordinate" workers).

Table 2.2 Probability of being employed in each employment category, male

	Fixed-term		Professionals		Self-employed		Atypical	
	b	se	b	se	b	se	b	se
EU born	-0.138	(0.085)	-1.179***	(0.315)	-0.115	(0.125)	-0.366	(0.233)
Extra-EU born	-0.161***	(0.052)	-1.231***	(0.237)	-0.202***	(0.076)	-0.759***	(0.141)
Age	-0.091***	(0.009)	0.173***	(0.024)	0.174***	(0.013)	0.053***	(0.018)
Age^2	0.001***	(0.000)	-0.001***	(0.000)	-0.002***	(0.000)	-0.000	(0.000)
Upper sec. degree	-0.458***	(0.031)	1.710***	(0.147)	0.201***	(0.043)	0.163**	(0.072)
Tertiary degree	-0.772***	(0.050)	1.847***	(0.157)	-0.253***	(0.065)	0.231**	(0.093)
Studying	0.703***	(0.050)	-0.049	(0.139)	-0.234***	(0.081)	1.246***	(0.092)
Exp. as open-ended	-0.246***	(0.006)	-0.528***	(0.017)	-0.251***	(0.007)	-0.307***	(0.012)
$Exp.^2$ as open-ended	0.004***	(0.000)	0.010***	(0.000)	0.005***	(0.000)	0.005***	(0.000)
Exp. as fixed-term	0.503***	(0.014)	-0.809***	(0.077)	-0.559***	(0.038)	-0.585***	(0.055)
$Exp.^2$ as fixed-term	-0.012***	(0.001)	0.049***	(0.005)	0.040***	(0.003)	0.039***	(0.004)
Exp. as self-employed	0.099***	(0.009)	-0.022	(0.025)	0.554***	(0.008)	0.209***	(0.014)
$Exp.^2$ as self-employed	-0.003***	(0.000)	-0.002**	(0.001)	-0.012***	(0.000)	-0.007***	(0.000)
Exp. as professional	-0.097***	(0.025)	0.561***	(0.017)	-0.044	(0.029)	-0.015	(0.029)
$Exp.^2$ as professional	0.001*	(0.001)	-0.015***	(0.001)	-0.001	(0.001)	0.000	(0.001)
Exp. as atypical	0.084***	(0.022)	0.077*	(0.041)	0.008	(0.026)	0.816***	(0.021)
$Exp.^2$ as atypical	-0.006***	(0.002)	-0.003	(0.003)	0.001	(0.002)	-0.031***	(0.002)
Constant	0.602***	(0.165)	-7.756***	(0.460)	-4.230***	(0.236)	-4.455***	(0.334)
Pseudo-R^2	0.507							
Nr of obs	140441							

Source: elaboration on AD-SILC data, coefficients in units of log odds. Omitted category in the dependent variable: permanent employees

Table 2.3 Probability of being employed in each employment category, female

	Fixed-term		Professionals		Self-employed		Atypical	
	b	se	b	se	b	se	b	se
EU born	-0.153**	(0.073)	-0.679***	(0.209)	-0.707***	(0.151)	-0.387**	(0.156)
Extra-EU born	-0.326***	(0.055)	-1.162***	(0.244)	-0.474***	(0.097)	-0.706***	(0.125)
Age	0.014	(0.010)	0.205***	(0.029)	0.191***	(0.019)	0.035**	(0.018)
Age^2	-0.000	(0.000)	-0.002***	(0.000)	-0.002***	(0.000)	-0.000	(0.000)
Upper sec. degree	-0.609***	(0.034)	1.173***	(0.166)	-0.026	(0.061)	-0.104	(0.073)
Tertiary degree	-0.906***	(0.044)	2.007***	(0.165)	-0.674***	(0.082)	0.053	(0.083)
Studying	0.681***	(0.048)	0.063	(0.129)	-0.218**	(0.107)	1.005***	(0.074)
Children aged 0-6	-0.221***	(0.039)	-0.368***	(0.121)	0.316***	(0.060)	-0.416***	(0.079)
Exp. as open-ended	-0.266***	(0.006)	-0.582***	(0.023)	-0.272***	(0.010)	-0.343***	(0.012)
$Exp.^2$ as open-ended	0.005***	(0.000)	0.012***	(0.001)	0.005***	(0.000)	0.007***	(0.000)
Exp. as fixed-term	0.568***	(0.013)	-0.867***	(0.086)	-0.778***	(0.052)	-0.545***	(0.046)
$Exp.^2$ as fixed-term	-0.019***	(0.001)	0.052***	(0.006)	0.050***	(0.003)	0.037***	(0.003)
Exp. as self-employed	0.101***	(0.012)	-0.024	(0.042)	0.595***	(0.011)	0.127***	(0.019)
$Exp.^2$ as self-employed	-0.003***	(0.000)	-0.000	(0.001)	-0.013***	(0.000)	-0.004***	(0.001)
Exp. as professional	-0.048**	(0.024)	0.636***	(0.029)	-0.048	(0.042)	-0.093***	(0.035)
$Exp.^2$ as professional	0.001	(0.001)	-0.019***	(0.002)	0.001	(0.002)	0.002	(0.001)
Exp. as atypical	0.057***	(0.020)	0.072	(0.044)	-0.046	(0.037)	0.794***	(0.024)
$Exp.^2$ as atypical	-0.002	(0.002)	-0.004	(0.003)	-0.001	(0.004)	-0.036***	(0.002)
Constant	-0.920***	(0.183)	-7.673***	(0.555)	-4.917***	(0.340)	-3.146***	(0.317)
Pseudo-R^2	0.455							
Nr di oss	110747							

Source: elaboration on AD-SILC data, coefficients in units of log odds. Omitted category in the dependent variable: permanent employees

These results are likely driven by the characteristics of private permanent employees, which represent a much larger share of the permanent employees than those working in the public sector and are on average younger and less educated than civil servants. For equal demographic characteristics, cumulated past work experience in any of the employment category increases chances of persistence in that type. However, some transitions between job types are still likely to occur. More years employed as fixed-term significantly increase the chances to improve workers own stability towards permanent contracts. An additional year of experience as professional increases the chances of becoming a permanent employee this year, as well as a longer experience as self-employed improves the chance to move towards atypical or fixed-term contracts. Finally, more cumulated years as atypical in the past makes it more likely to be a fixed-term or professional this year. For females, it is worth noting that being a mother of at least one young child decreases the likelihood of being employed in any of the possible employment categories with respect to permanent employees, with the exception of self-employment.

Table 2.4 reports regression results for working pensioners, both males and females. The choice of predictors reflects the smaller sample and the peculiarity of working pensioners. Those having a partner that is also working (whether retired or not) and those with a cumulated past experience in self-employment are more likely to be self-employed in time *t*. This result may be driven by the fact that artisans, dealers and farmers may more likely run family businesses compared to the other categories[23]. Instead, those who retired early are more likely to be employed as private permanent employees or with atypical contractual arrangements with respect to self-employed. All kinds of cumulated past experience in the labour market increases the likelihood of keeping on working in the same employment category, especially for self-employed. Furthermore, additional years of cumulated past experience as a public permanent employee increases the likelihood of being employed as an atypical type of worker, but not vice versa. Instead, a longer experience as a fixed-term employee leads more likely to open-ended arrangements or atypical arrangements than to self-employment. Finally, a higher income increases the likelihood of working with atypical arrangements and decreases the probability of being employed as a private permanent employee with respect to self-employed.

[23] According to Cerved (2018), 50% of SME operating in agriculture and 62% of those operating in services in Italy are family-owned businesses.

Table 2.4 **Probability of being employed in each employment category, working pensioners**

	Open ended private		Atypical	
	b	se	b	se
Partner working	-0.412**	(0.176)	-0.798***	(0.195)
Early retirement	0.334*	(0.171)	0.213	(0.178)
Exp. as open-ended private	0.063***	(0.008)	0.003	(0.008)
Exp. as open-ended public	0.072*	(0.041)	0.085**	(0.042)
Exp. as fixed-term employee	1.827**	(0.767)	1.867**	(0.767)
Exp. as self-employed	-0.098***	(0.008)	-0.143***	(0.009)
Exp. as atypical	-0.112*	(0.058)	0.310***	(0.028)
5' income quintile	-0.690***	(0.157)	0.354**	(0.176)
Constant	-0.188	(0.353)	-0.007	(0.377)
Pseudo-R^2	0.553			
Nr of obs	4824			

Source: elaboration on AD-SILC data, coefficients in units of log odds. Omitted category in the dependent variable: self-employed

2.2.3 Months and monthly wages

Once the work type is determined, we assume that self-employed, professionals and permanent employees work all year, because for the first two categories it is not possible to obtain a precise estimate of months worked from AD-SILC data and among the last one those working only part of the year are a group that is quite an exception. For fixed-term employees and atypical ones, we first determine who is working 12 months. For the rest we estimate the number of months worked. Then, we estimate real[24] monthly wages[25], separately for each of the employment categories simulated in the model, but grouping together fixed and open-ended contractual arrangements in private and public employees. For all estimates of this subsection, we use random-effects models. Indeed, in this case we are able to import into the

[24] Nominal earnings are converted into real earnings at the constant prices of 2015.

[25] Wages are defined as the sum of the overall income earned over the year, attributed all to the employment category to which the worker is assigned, even if part of the labour income comes from a different typology of work. This is because in the model only one type of job over a year is allowed but we want to avoid underestimation of yearly labour incomes. Possible amounts received as indemnities for maternity, sickness or job suspension are included.

microsimulation model the same individual heterogeneity we are taking into account of in the econometric estimates[26].

Table 2.5 shows the estimated coefficients for the number of months worked, by sex. For equal features on the labour market, foreigners, fathers of young children[27] and more educated individuals are working for more months within a year. Everything equal concerning demographic characteristics, fixed-term public employees (the omitted category) work more months than both fixed-term private employees and atypical workers. Also, those working in the past year and those with more experience are employed for a higher fraction of the year.

As illustrative of all wages estimate, we show here regression results for private employees. All other categories show similar patterns. Table 2.6 shows the estimated coefficients. Looking at demographic characteristics, higher educated individuals and fathers[28], even a few years away from the birth, are associated with higher wages. Instead, foreigners of all nationalities earn less than natives; their advantages on the labour market highlighted previously does not extend to wages. Motherhood penalises women in terms of earnings not only close to birth but even once children have grown up, in line with the recent literature claiming the importance of the "motherhood penalty" in explaining a significant proportion of the gender pay gap[29].

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26 In the simulation program we use predicted values of the random effects for in-sample individuals, while for new-born or out-of-sample individuals we impute these values, drawing from a normal distribution with the estimated standard deviation.

27 Some scholars find evidence of a fatherhood wage premium, see next note. Similar mechanisms may explain fathers' longer period of work within a year.

28 Some scholars find evidence of a fatherhood wage premium, but it is generally modest in size and detected only in some contexts. Possible explanations of this premium lie in individual changes in work efforts because of parenthood, couple specialization and employer discrimination. See for example Mari (2019).

29 Recent literature emphasizes the role of parenthood as the main cause of gender disparities both in terms of labour market participation and earnings differentials between men and women. See XIX Rapporto Annuale INPS and Martino (2017) for Italy. See Kleven *et al.* (2019) and Bertrand (2020) for a review.

Table 2.5 Number of months worked

	Male		Female	
	b	se	b	se
Foreign	0.184**	(0.092)		
Retired	-0.816***	(0.153)	-0.764***	(0.192)
Studying	-1.193***	(0.088)	-0.701***	(0.076)
Children aged 0-6	0.310***	(0.087)		
Upper sec. degree	0.558***	(0.060)	0.516***	(0.059)
Tertiary degree	1.034***	(0.096)	1.282***	(0.079)
Fixed-term private employee	-1.465***	(0.143)	-1.448***	(0.084)
Atypical	-2.474***	(0.153)	-2.487***	(0.095)
Working (lag)	1.431***	(0.055)	1.624***	(0.050)
Experience	0.080***	(0.008)	0.068***	(0.009)
Experience^2	-0.001***	(0.000)	-0.001***	(0.000)
Constant	4.405***	(0.177)	3.963***	(0.135)
σ_u	2.228		2.025	
σ_e	1.850		1.883	
ρ	0.592		0.536	
R^2-within	0.075		0.068	
R^2-between	0.171		0.217	
R^2-overall	0.147		0.182	
Nr of obs	14687		16633	

Source: elaboration on AD-SILC data

Table 2.6 Log of monthly wages, private employees

	Male		Female	
	b	se	b	se
EU born	-0.041***	(0.012)	-0.131***	(0.011)
Extra-EU born	-0.103***	(0.007)	-0.185***	(0.009)
Upper sec. degree	0.123***	(0.004)	0.124***	(0.004)
Tertiary degree	0.325***	(0.008)	0.264***	(0.007)
Children aged 0-3	0.034***	(0.004)	-0.024***	(0.005)
Children aged 4 and over	0.023***	(0.004)	-0.025***	(0.005)
Exp. as private employee	0.034***	(0.001)	0.021***	(0.001)
Exp. as private employee^2	-0.000***	(0.000)	-0.000***	(0.000)
Open-ended contract	0.025***	(0.005)	0.010**	(0.004)
Part-time	-0.053***	(0.008)	-0.021***	(0.004)
Partner working	0.024***	(0.003)	0.016***	(0.003)
Constant	7.210***	(0.007)	7.217***	(0.007)
σ_u	0.359		0.310	
σ_e	0.142		0.137	
ρ	0.866		0.836	
R^2-within	0.021		0.016	
R^2-between	0.337		0.254	
R^2-overall	0.323		0.244	
Nr of obs	88909		63861	

Source: elaboration on AD-SILC data

Concerning labour market features, longer experience and open-ended contracts are associated with higher wages, as expected. Individuals whose partners are working benefit from higher salaries, confirming the assortative mating pattern that had already emerged in Table 2.1. Instead, working part-time causes a wage penalty, a result common in the literature[30].

[30] See O'Dorchai *et al.* (2007) and Golden (2020) for a review.

2.3 Pension Module

2.3.1 Public pensions

Figure 2.3 illustrates the essential structure of the Pension Module in T-DYMM 3.0, which largely draws from the experience of previous releases of the model.

Workers contribute to the first (public) pension pillar on a mandatory base, with contribution rates set accordingly to the employment category assigned in the Labour Market Module. Every year, a potential pension benefit is computed according to the pertinent pension regime.

Present contributors to the pension system can be divided into two main categories[31]:

- "(Pure) NDC" (*contributivo puro*), for workers with no seniority prior to 1996, for whom benefits are entirely calculated according to Notinal Defined Contribution (NDC) rules[32];
- "Mixed" (misto), divided into:
  - "Mixed 1995", for workers with less than 18 years of seniority in 1995, for whom benefits are calculated according to the NDC rules pro rata for all years of seniority following 1995;
  - "Mixed 2011", for workers with at least 18 years of seniority in 1995, for whom benefits are calculated according to the NDC rules pro rata for all years of seniority following 2011.

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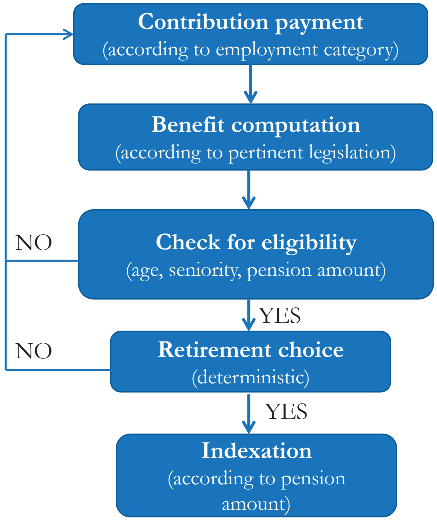
31 Further specification for "*Misto A*" and "*Misto B*" and for public sector workers are taken into account within the model.

32 NDC computation rules were first introduced by Law 335/1995 (the so-called "Dini Reform") and then extended to all workers by Decree Law 201/2011, converted into Law 214/2011 (the so-called "Fornero Reform").

Figure 2.3 Structure of the Pension Module, public pensions (1st pillar)



While present contributors all compute at least a portion of their pension benefit according to NDC rules, a very consistent portion of present retirees receives a pension that was entirely calculated according to the old Defined Benefit (DB) rules. After potential benefits are computed, individuals are checked for retirement eligibility. Table 2.7 illustrates the various modalities to access retirement according to the Italian legislation, as simulated in T-DYMM 3.0.

Age requirements for "Old Age 1", "Old Age 2" and "Old Age 3" criteria and seniority requirements for "Seniority" and "Seniority - young workers" criteria are updated every two years in line with variations in life expectancy at 65 years of age, as established by Law 122/2010. Decree Lay 4/2019, converted into Law 26/2019, has suspended updates to life expectancy variations until 2026 for the seniority requirements of "Seniority" and "Seniority – young workers" criteria. "Seniority – Quota 100" was introduced in 2019 and is set to be discontinued from 2022 onwards.

Table 2.7 Eligibility requirements for retirement as simulated in T-DYMM 3.0

Criteria	Regime	Requirements		2021
Old Age 1	NDC	age		64 years
		seniority		20 years
		amount		2.8 * *assegno sociale*[33]
Old Age 2	NDC, mixed	age		67 years[34]
		seniority		20 years[35]
	NDC	amount		1.5 * *assegno sociale*
Old Age 3	NDC	age		71 years
		seniority		5 years
Seniority	NDC, mixed	seniority	males	42 years, 6 months
			females	41 years, 6 months
Seniority – young workers	mixed	seniority		41 years, 12 months accrued before turning 19
Seniority – *Quota 100*	mixed	age		>62 years
		seniority		>38 years

T-DYMM 3.0 does not simulate retirement according to the so-called "*APE*" criterion, introduced in 2017 and discontinued in 2020 after limited adhesions, nor the *"Opzione donna*" criterion, by which female workers belonging to the "Mixed" regime may access retirement many years in advance (58 years of age as of 2021) if they choose to switch entirely to NDC computation rules. The reasons for the exclusion of "*Opzione donna*" will be clear as we discuss the simulation of retirement decisions. In T-DYMM 3.0, retirement decisions are purely deterministic. In the Baseline scenario, we assume that individuals access retirement as soon as they are entitled to. Such an assumption may seem acceptable as of today, as age requirements have risen rapidly in the past few years, especially for women. However, as Notional Defined Contribution (NDC) rules phase in, average pensions are expected to decrease and a strong economic incentive to postpone retirement to increase benefits (both by increasing contributions accrued and by reducing life expectancy at retirement) will kick

[33] The *assegno sociale* is the social allowance for the elderly (see Par. 2.5).

[34] Starting from 2018, the age requirement for the "Old age 2" criterion coincides with the age requirement for the *assegno sociale*.

[35] 15 years are enough for workers with at least 15 years of seniority as of Dec 31st, 1992.

in. By assuming that workers retire as soon as possible, we are implicitly assigning all workers a stronger preference to spending more time in retirement rather than getting a higher benefit. A behavioural function that differentiates among different profiles may provide a better representation of reality and we are working on its development for the next release of T-DYMM.

In the meantime, in the present report we complement results for the Baseline scenario with a limited set of indicators computed on a "Choice" scenario, where workers who meet retirement criteria do not automatically retire, but first assess their standing in terms of a potential replacement rate (here computed as ratio between potential benefit and average of the last five salaries). If the individual potential replacement rate is at least equal to the Aggregate Replacement Ratio (ARR) measured by Eurostat in 2015 (baseline year for the simulations)[36], or if workers are unemployed, they retire; otherwise, they keep working until they reach the age requirement for the "Old Age 3" criterion[37]. An exception is made for workers of the public sector, as the pertinent legislation mandates that, if public workers meet retirement eligibility requirements and are past a given age limit ("*limite di età ordinamentale*", which for most public workers stands at 65 and is not updated to variations in life expectancy), they must retire.

Once workers access retirement, their pension is indexed to price inflation[38] according to the pertinent legislation, which only allows full indexation to pensions below a certain threshold amount (in 2021, below € 20,000 annually). For the period 2019-2021, an *ad hoc* temporary reduction on pensions above € 100,000 annually (so-called *"pensioni d'oro*) is also in place.

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[36] The ARR is the ratio of the gross median individual pension income of the population aged 65-74 relative to the gross median individual labour income of the population aged 50–59, excluding other social benefits. In 2015, the value registered for Italy by Eurostat, irrespective of gender, is 66%.

[37] Decree Law 201/2001, converted into Law 214/2011 specifically states that workers are incentivised too keep working until such age limit and, to that end, are entitled to the same rights in terms of employment protection as workers who do not meet retirement eligibility.

[38] For historical data, we use the FOI index series (the Italian consumer price index for blue- and white-collar worker households), in accordance with the pertinent legislation; for projection data, we rely on the projections underlying the 2021 Ageing Report on the Consumer Price Index.

Besides seniority and old-age pensions (work-related pensions), in the Pension Module we also simulate the supplementation to a minimum amount (in place for pensions of workers belonging to the "Mixed" regime), inability pensions for workers that fall ill or disabled and survivor pensions.
For inability pensions, we simulate the legislation put in place by Law 222/1984, which introduced the *Assegno ordinario di invalidità*, for severely disabled workers, and the *Pensione di inabilità*, for workers unable to work because of disability. Individual probabilities to receive these benefits are based on regression parameters estimated on AD-SILC, which highlight the high persistency of the phenomenon and the relevance of the disability status (simulated in the Demographic Module; see Par 2.1). Average probabilities to receive inability pensions are aligned by gender and 5-year age class to INPS data available for the period 2016-2019; beyond 2019, probabilities are projected following the same logic adopted for disability probabilities (which on turn follow the Reference Scenario of the 2021 Ageing Report; see Par. 2.1). Table 2.8 summarises all benefits simulated within the Pension Module.

Table 2.8 Simulation of pension benefits in T-DYMM

Old-age and seniority pensions
Supplementation to a "minimum amount" (*Integrazione al trattamento minimo*)[39]
Survivor pensions (*Pensione di reversibilità* and *pensione indiretta*)
Inability pensions (*Assegno ordinario di invalidità* and *Pensione di inabilità*)
Private pensions (2nd and 3rd pillars)

[39] The "minimum amount" (*trattamento minimo*) is a threshold amount (€ 515 in 2020) paid out to pensioners belonging to the DB and Mixed regimes. Even though it is bound to extinguish once the transition to the NDC scheme is completed, the *trattamento minimo* is used as benchmark for indexation rules and for the computation of a number of benefits.

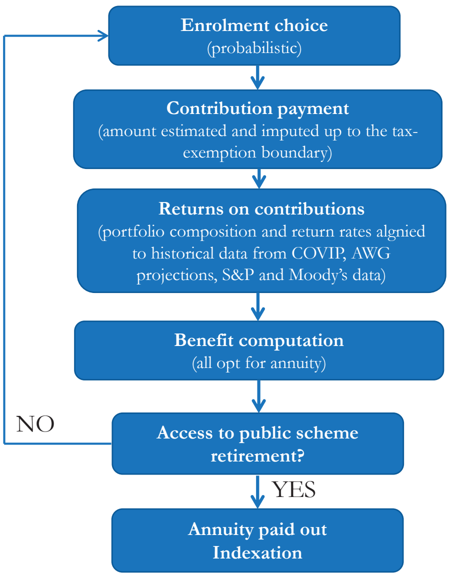
2.3.2 Private pensions

Building on the experience of T-DYMM 2.0, T-DYMM 3.0 also comprises a sub-module on private pensions. Figure 2.4 illustrates its structure.

Unlike what happens in the 1st Pillar, workers participate in private plans on a voluntary basis. Individual probabilities are based on regression parameters estimated on AD-SILC (SHIW data), which highlight the role of age, labour income, financial literacy, education, employment category, net wealth and impose a high level of persistence on the phenomenon. Average probabilities to contribute are aligned, irrespective of age and gender, according to COVIP data; in projection years, average probabilities are kept constant to the latest available figures (2020).

Contributors to the 2nd pillar (collective funds, *fondi negoziali*) may devolve their TFR (*Trattamento di Fine Rapporto*, end-of-service allowance[40]) and voluntary contributions, while for the 3rd pillar (either open funds, *fondi aperti*, or individual pension plans, *piani individuali pensionistici*) contribution to the fund may vary yearly depending on labour income and net wealth.

Figure 2.4 Structure of the Pension Module, private pensions (2nd and 3rd pillars)



[40] For a description of the *Trattamento di Fine Rapporto*, see Par. 7.2.7 of MEF *et al.* (2020).

Investments in the 2nd and 3rd pillar produce returns that are computed following COVIP data when available (2016-19) and projections based on the portfolio composition of pension funds and on assumptions regarding portfolio components for the rest of the simulation period (for a description of the assumptions on various financial assets, see Par. 2.4).
When individuals access retirement in the public pillar, they are also assigned an annuity (if any investment is present) from the 2nd and 3rd pillars, which is henceforth indexed.

2.4 Wealth Module

One of the main novelties of T-DYMM 3.0 regards the introduction of a Wealth Module that accounts for household wealth dynamics. Modelling private wealth may provide a more complete picture of disposable income and households' well-being distribution before and after retirement.
We define net wealth as the sum of real and financial wealth to which we subtract liabilities. Private pensions are considered an additional form of wealth accumulation collected at retirement. The property of houses is the only form of real wealth. Finally, financial wealth is divided into four different activities: liquidity, government bonds, corporate bonds and stocks.
The structure of the Wealth Module is based on Tedeschi *et al.* (2013). It is composed of different processes, which are illustrated in the scheme in Figure 2.5. The scheme summarizes the multiple processes that are included in the Wealth Module in T-DYMM 3.0. The processes in the model are sequential, as presented from top to bottom in the scheme, although they are often related amongst one-another. For instance, the acquisition of house wealth implies a reduction in the level of financial wealth, the opposite in case of selling. Every step of the Wealth Module foresees the presence of choices taken at the household level that are modelled with regressions and aligned.
The estimates adopted in the model are based on SHIW micro-data (waves 2002-2016). We use discrete choice models (logit) for discrete transitions (for instance buying/selling houses, receiving intergenerational transfers, making donations, renting the second dwelling), log-continuous regressions or continuous regressions for quantities (either levels or ratios of income or financial wealth). In Table 2.9 we list all the regressions.
As mentioned above (see Par. 1.2), alignments are a key part of a dynamic micro-simulation model. Even though it is hard to find good alignments for wealth components and processes because of the lack of information on this topic, we have decided to align some specific processes for which external data sources are available. We use data from ISTAT and the Department of Finance; when discussing the single processes we mention the data source in case the process is aligned.

Table 2.9 Regressions adopted in the module

Process	Regression dependent variable	Data source
Financial investment decision	Ownership of government bonds	SHIW 2010-16
Financial investment decision	Ownership of corporate bonds	SHIW 2010-16
Financial investment decision	Ownership of stocks	SHIW 2010-16
Financial investment decision	Ratio of liquidity over total financial wealth	SHIW 2010-16
Financial investment decision	Ratio of government bonds over total financial wealth	SHIW 2016
Financial investment decision	Ratio of corporate bonds over total financial wealth	SHIW 2016
Financial investment decision	Ratio of stocks over total financial wealth	SHIW 2016
Inter vivos transfers	Probability of making transfers	SHIW 2014
Inter vivos transfers	Amount transferred (absolute value)	SHIW 2014
Inter vivos transfers	Probability of receiving transfers	SHIW 2014
Inter vivos transfers	Amount received (absolute value)	SHIW 2014
Inheritance	Probability of receiving inheritance	SHIW 2014
Inheritance	Amount received (absolute value)	SHIW 2014
Financial literacy	Financial literacy level assignment	SHIW 2016
House investment decision	Probability of buying house	SHIW 2010-16
House investment decision	Log-value of purchased house	SHIW 2010-16
Rent	Probability of rent paid for households who do not own house wealth	SHIW 2010-16
Rent	Ratio of rent paid over household income	SHIW 2010-16
Rent	Probability of rent received for households who own second houses	AD-SILC 2015
Rent	Ratio of rent received over household income	AD-SILC 2015
Consumption	Log-level of household consumption	SHIW 2002-16

In the second part of this paragraph, we discuss the processes that are part of the Wealth Module in greater detail.

2.4.1 Private wealth transfers

The starting processes are the one of intergenerational transfers, *inter vivos* (donations) and *mortis causa* (inheritances). The inheritance is driven by demography in the sense that the total amount of wealth transferred equals the wealth of the deceased; then the receivers are selected deterministically, if related to the deceased individual, or probabilistically through regressions based on SHIW[41]. The *inter vivos* transfers are modelled based on SHIW regressions on both sides of the donors and the recipients; the number of households who donate and who receive and the totals donated and received are aligned between each other.

2.4.2 Wealth update

The second process is the one updating the amounts of wealth. Initially, the household savings and the possible collected TFR are summed up, subsequently the values of house wealth and financial wealth evolve over time depending on the level of inflation and the return rates. The different return rates on the various forms of wealth are summarized in Table 2.10 The value of house wealth evolves following the GDP growth; for the government bonds we relied on the implicit return rate on debt provided by AWG. For corporate bonds and stocks we divided between income and capital gain, in the simulation years covered by actual data we use information from S&P 500, for the future we use the GDP growth projections for OECD countries as a proxy of the income gain for both these financial activities and we assign the stock-owners an extra amount of return in terms of capital gain that equals the historical level of mark-up between stocks and corporate bonds. The evolution of the capital gain is taxed yearly by 0.26% (for stocks we assume complete mobility of the financial portfolio, whereas for corporate bonds we assume the mobilization of half of the bonds owned).

Returns on financial and real investments change over time but do not vary within the sample. For future releases of T-DYMM, we are working on including some variability across return rates, as well as on sensitivity scenarios regarding average rates.

[41] At the start of the simulations, for all individuals living outside of their original household we do not have information on their parents, hence we have to simulate inheritances probabilistically.

Table 2.10 Return rates, adopted methodology

Wealth type		2016-20	2021-70
House wealth		GDP growth	GDP growth
Financial wealth			
Government bonds		Implicit rate on debt AWG	Implicit rate on debt AWG
Corporate bonds	Income gain	S&P 500	GDP growth OECD countries
	Capital gain	S&P 500	0
Stocks	Income gain	S&P 500	GDP growth OECD countries
	Capital gain	S&P 500	Mark-up stocks-bonds
Mortgages		Long-term interest rate AWG	Long-term interest rate AWG

2.4.3 House ownership

The next process concerns house ownership. Every household has a probability of buying and selling a house based on regressions estimated on SHIW. The number of houses bought equals the number of houses sold and these values are aligned to the national statistics from ISTAT. The value of the houses sold are deterministically computed within the model whereas the value of the houses bought are computed through regressions, however the total value of houses bought equals the total value sold. The acquisition of the house is financed with the down-spending of financial wealth, the accrued TFR (70% of the total, in line with the pertinent legislation) and finally with mortgages (they constitute the only form of liability in the model). The values of mortgages are adjusted for households whose potential mortgage payment surpasses 60% of household income.

An extra process that is connected to house wealth is the one of rent, which implies the income production of additional dwellings and an expenditure for households who are not houseowners. The choice whether to rent or not the additional house (it is not possible to rent the first house), is modelled with a regression based on AD-SILC data (the information taken from Tax returns makes it possible to study this choice). The households that do not own a house may or may not live in a rented house (the possibility of loan to use is taken into account); to model this circumstance we use a regression based on SHIW. The amount of rent received and paid are simulated as ratios to the household income.

2.4.4 Financial investment decision

Financial investment decisions are crucial in the module. As said above, there are four different types of financial activities. The current process is modelled in two steps: first of all, we simulate ownership and second the amount owned. We model the choice of whether to invest in government bonds, corporate bonds and stocks through dynamic regressions based on SHIW. We show the results of our regression estimates, based on SHIW 2010-16, in Table 2.11. The dependent variables are the probabilities of investing in one of the three forms of financial activities, FA, since we assume that households who own financial wealth always have a positive probability of detaining liquidity. In particular, we have the situation in which FA2 corresponds to government bonds, FA3 corresponds to corporate bonds and FA4 corresponds to stocks. In order to correctly estimate the dynamic relationship between ownership at time t and at time t-1 we check for the initial conditions in the status (whether the household owned the financial activity in 2010) and we average the time-varying variables, following the approach by Wooldridge (2005). In the simulation we do not use the initial conditions and averages coefficients, but we consider them as good instruments to improving the precision of coefficients of the lagged dependent variable[42].

The division of total financial wealth in the various activities is made with regressions based on SHIW 2016 that have the ratio of the single activity amount over the total as a dependent variable and use information on the level of financial literacy of the head of the household as an explanatory variable.

As the next steps in our research, we want to improve the econometric specification taking into account the simultaneity of financial choices and the possible selection bias in the estimates of the amount invested in each financial instrument (possibly using a Heckman two-step procedure or a Tobit model).

42 Moreover, in the simulation we adopt a simplified version of the regression checking for quartiles of financial wealth.

Table 2.11 **Probability of investing in financial activities (government bonds, corporate bonds, stocks)**

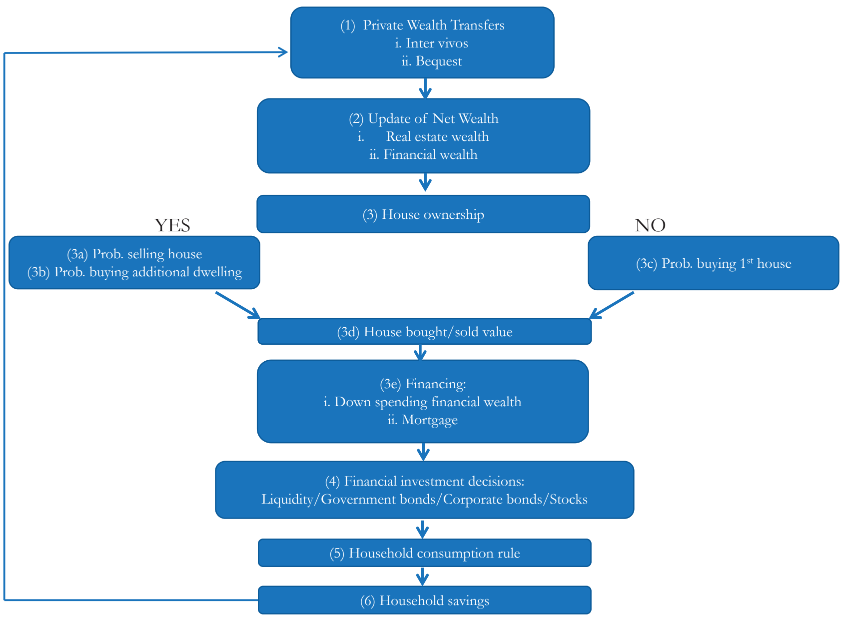
	$FA2_t$		$FA3_t$		$FA4_t$	
	b	se	b	se	b	se
FA2 $_{t-1}$	1.662***	(0.041)				
FA2 $_0$	0.886***	(0.033)				
FA3 $_{t-1}$			1.296***	(0.185)		
FA3 $_0$			0.899***	(0.187)		
FA4 $_{t-1}$					1.350***	(0.143)
FA4 $_0$					0.741***	(0.145)
Age	-0.026	(.)	-0.099***	(.0.021)	-0.038**	(0.017)
Log_fin_wealth	1.603***	(0.020)	2.230***	(0.088)	1.328***	(0.057)
Avg_age	0.056***	(0.052)	0.079***	(0.022)	-0.005	(0.017)
Avg_fin_wealth	-0.134**	(0.096)	-0.197**	(0.085)	0.014	(0.068)
Female	0.337***	(0.120)				
Degree	-0.776***	(0.088)			0.299**	(0.117)
Constant	-19.730***	(0.027)	-22.684***	(0.855)	-13.969***	(0.522)
Pseudo-R^2	0.654		0.774		0.639	
Nr of obs	6019		6019		6019	

Source: elaborations on SHIW 2010-16

2.4.5 Household consumption rule

The last process in the Wealth Module is the household consumption decision. This process is one of the most relevant since household savings are reintroduced in the model the following year in the form of financial wealth (as represented by the arrow connecting the last box to the first one in Figure 2.5). At the end of the simulation period, every household is endowed with an amount of disposable income and we confer a certain level of consumption that may or may not exceed the household disposable income; in the first case, the household will use the financial wealth as a supplementary source to finance its expenditure. Consumption levels are determined through a panel regression based on SHIW 2002-16. Results are shown in Table 2.12. The dependent variable is the logarithm of consumption. We adopt a fixed effects estimator, where the correlation between error component and unobserved time-invariant household effect is introduced in the simulation. The main explanatory variables are the level of household income (inserted in deciles) and of financial wealth (in quintiles); the regression coefficients illustrate a positive correlation between those two variables and consumption, as expected. The number of components and of income earners increase the total consumption level, whereas the retired status of the head of the household reduces consumption and, therefore, increases savings. This result, typical of Italy, is known in the literature as the "retirement consumption puzzle" (see Battistin *et al.* 2009).

Figure 2.5 Structure of the Wealth Module



The results of the regression estimates present an issue related to the difference between micro data and macro aggregates on consumption and savings. As well-known in the literature (Cifaldi and Neri 2013), the discrepancy between the savings rate obtained from SHIW data and the one obtained from Financial Accounts is large; therefore, our choice is to align the average level of consumption to the national savings rate. For the initial years of the simulation we use actual data from ISTAT (in 2019, the savings rate equals 9.8%). The projection is made using a logarithmic function (by 2070, the savings rate has decreased to 8.25%).

The future developments of the project will focus on the introduction of life-cycle components in the estimate of consumption function taking into account the permanent income hypothesis (possible behavioural changes in household savings). From an econometric point of view, we will concentrate on improving the estimates of the household consumption behaviour by using IV estimations to correct for income endogeneity (due to simultaneity and measurement error).

Table 2.12 Panel estimates of log-consumption

	b	se
Age	0.011***	(0.001)
Income_dec=2	0.213***	(0.012)
Income_dec=3	0.304***	(0.013)
Income_dec=4	0.375***	(0.014)
Income_dec=5	0.447***	(0.015)
Income_dec=6	0.516***	(0.016)
Income_dec=7	0.575***	(0.016)
Income_dec=8	0.653***	(0.018)
Income_dec=9	0.690***	(0.019)
income_dec=10	0.777***	(0.022)
Fin_wealth_quint=2	0.037***	(0.008)
Fin_wealth_quint=3	0.056***	(0.008)
Fin_wealth_quint=4	0.075***	(0.009)
Fin_wealth_quint=5	0.118***	(0.011)
No. components	0.038***	(0.006)
Retired	-0.067**	(0.011)
No. earners	0.035***	(0.007)
Constant	8.176***	(0.045)
σ_u	0.382	
σ_e	0.354	
ρ	0.538	
R^2-within	0.146	
R^2-between	0.459	
R^2-overall	0.381	
Nr of obs	39559	

Source: elaborations on SHIW 2002-16

2.5 Tax-Benefit Module

At the lowest level of the model hierarchy comes the Tax-Benefit Module, which simulates taxes paid and benefits granted at the national level (according to the legislation of 2020).

T-DYMM does not encompass an internal migration module and thus does not allow individuals to move between regions or municipalities. As a result, we opted for not simulating regional- and municipal-level taxes and transfers. This is motivated partly because non-national measures can differ substantially from one another, which would in turn affect the validity of our results under the assumption of no internal movements; and partly due to the lack of information needed for an accurate replication.

The module performs the calculation of social insurance contributions (SICs), direct taxes on different income sources (i.e., labour and retirement income, capital income, rental income), and in-cash social transfers, both means-tested and non-means-tested payments.

In what follows we provide a brief overview of the module's structure by focusing on its sequence and coverage in terms of simulated measures, as well as methodological implementation.

2.5.1 SICs and taxes

The starting process of the Tax-Benefit module is the calculation of SICs, which draws largely on the Italian country component of the EUROMOD model, to which reference is made for a more detailed explanation (Surtherland and Figari 2013). We simulate employer and employee contributions collected for the payment of inability, old-age/seniority and survivors' pensions, as well as contributions related to the payment of unemployment benefits, redundancy pay, sickness and maternity pay and family allowances. We also simulate contributions paid by self-employed workers.

Following the sequence of the module, we then move to the computation of proportional taxes (see full list in Table 2.13). Even though the personal income tax contributes by far the most to the redistributive effect of the Italian tax-benefit system (Boscolo 2019), proportional taxes have grown significantly in recent years. In fact, a greater share of self-employment income and rental income previously included in the PIT base is now excluded and subject to proportional taxation. Self-employed workers can opt for substitute tax regimes conditional on certain income and organisational criteria, as well as individuals regardless of their working status can subject rental income from residential properties to more favourable taxation rather than to the personal income tax. In both cases, we select individuals in the simulation by using logistic regression analyses on micro data from Tax returns for 2015 among those who meet statutory requirements.

Furthermore, income sources exempt from progressive taxation are relevant when it comes to the calculation of social transfers, given that they are considered in the means test of many social transfers.

As for the personal income tax, it is worth specifying how deductions and tax credits are calculated. The implemented strategy is in line with previous experiences in microsimulation studies (see above all Albarea *et al.* 2015). While the most sizeable tax expenditures in terms of granted tax relief are fully simulated by the model[43], both with regard to beneficiaries and amount, we determine beneficiaries of residual tax expenditures[44] by using logistic regression analyses on pooled micro data from Tax returns covering a 7-year interval (2009-2015) and then calibrate amounts with aggregate statistics by income groups. For each calibrated tax expenditure, potential beneficiaries are selected among those with relevant characteristics for eligibility. This procedure allows for a more precise simulation of the personal income tax and overall net liabilities. At the same time, given the growing attention that is being paid to reforming the system of direct taxation in Italy, it contributes to making T-DYMM a reliable tool that could add to the current discussion by focusing on mid- and long-term redistributive effects of proposed tax reforms.

Table 2.13 Simulation of SICs and taxes in T-DYMM

SICs: • employer social insurance contributions • employee social insurance contributions • contributions paid by self-employed workers
Proportional taxes and tax regimes that substitute the personal income tax on: i. capital income: government securities, bonds and shares ii. private pensions: II and III pillars iii. self-employment income subject to *regime fiscale di vantaggio** or *regime forfetario*** iv. rental income subject to *cedolare secca* (assigned to the head of the household)** v. premi di produttività**
Personal income tax (*Imposta sul reddito delle persone fisiche* – IRPEF)***

Note: * Recipients are bound to gradually diminish to zero under current legislation. We assume that there are no recipients by 2030; ** Recipients are aligned to aggregate administrative data in the 2016-2019 interval, while from 2020 onwards we align recipients by taking as reference their external total as of 2019 and update it to: the population growth at the individual level as for ii; the population growth of self-employed workers as for iii; the population growth at the household level as for iv; the population growth of employees as for v; *** Recipients of residual tax expenditures are aligned to external totals from (weighted) Tax returns micro data for the 2015 tax period, annually updated to the population growth of gross PIT income's recipients.

[43] As for deductions, we refer to social insurance contributions paid by self-employed workers, cadastral value of the main residence, and contributions to private pension plans; regarding tax credits, the most relevant ones are the tax credit for labour and retirement income and tax credits for dependent family members.

[44] Such as social insurance contributions paid for domestic help, donations to religious institutions, health-related expenses, mortgage interest payments, education-related expenses and so on.

2.5.2 In-cash benefits

Subsequent to the simulation of SICs and taxes, the module performs the calculation of in-cash benefits by following the order of appearance listed in Table 2.14.

In its current version, T-DYMM assumes the full take-up rate for each benefit except for disability allowances. We are aware that this assumption is far from reality and further research efforts are necessary. In this respect, we will explore how to estimate and model take-up rates separately for each simulated measure, while at the same time trying to identify patterns in the reception of two or more benefits on observable characteristics.

Table 2.14 Simulation of in-cash benefits in T-DYMM

• Unemployment benefits (*NASpI* and *DIS-COLL*)*
• In-work bonus for employees and atypical workers ("*Bonus IRPEF*", which has replaced "*Bonus 80 euro*")
• Means-tested disability allowances (*Pensione di inabilità agli invalidi civili* up to Standard Pensionable Age and *Assegno sociale sostitutivo* afterward)**
• Non-means-tested disability allowances (*Indennità di accompagnamento* for those aged 18 or above and *Indennità di frequenza* for those aged below 18)**
• War pensions and indemnity annuities (*Rendite indennitarie*)***
• 14th month pension
• Social allowance for the elderly and related increases (*Assegno sociale* and *Maggiorazioni sociali*)
• Increases to inability, old-age/seniority and survivor pensions (*Maggiorazioni sociali del minimo*)
• Family allowances for employees' and pensioners' households (*Assegno al nucleo familiare*), which will be replaced by a more comprehensive measure from 2022****
• Newborn bonus (*Bonus Bebè*)
• Mother bonus (*Bonus Mamma*, from 2017 onwards)
• Minimum income schemes: - SIA (*Sostegno all'inclusione attiva*, 2017) - REI (*Reddito di Inclusione*, 2018) - RdC (*Reddito di cittadinanza*, from 2019 onwards)

Note: * Unemployment benefits are actually simulated prior to the Tax-Benefit Module, because they are subject to the personal income tax.; ** ** Average probabilities to receive disability allowances are aligned by gender and 5-year age class to INPS data available for the period 2016-2019; beyond 2019, probabilities are projected following the same logic adopted for disability probabilities (which in turn follow the Reference Scenario of the 2021 Ageing Report; see Par. 2.1); *** Recipients in T-DYMM's base year will hold these benefits until death. New occurrences are not simulated; **** Not yet simulated in the current version of the model. The new allowance will also replace tax credits for dependent children, the newborn bonus and the mother bonus.

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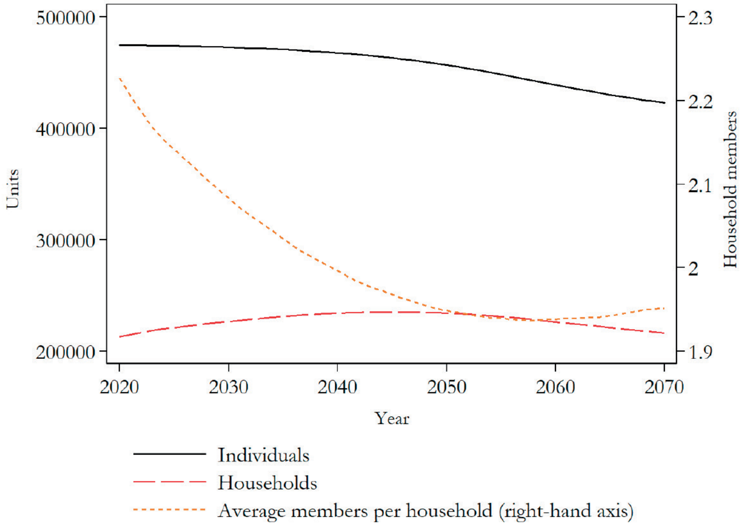
3. Results

In the present section of the report, we present the main findings of T-DYMM 3.0 for the simulation period 2020-2070, whose structure and data, extensively discussed in MEF *et al.* (2020), have been briefly reintroduced to the reader in the previous sections. We focus on the results produced in the Baseline scenario; in order to highlight the relevance of retirement choices and to contextualize future work on the matter, we have also produced a few indicators on the alternative Choice scenario.

3.1 Demographic Module

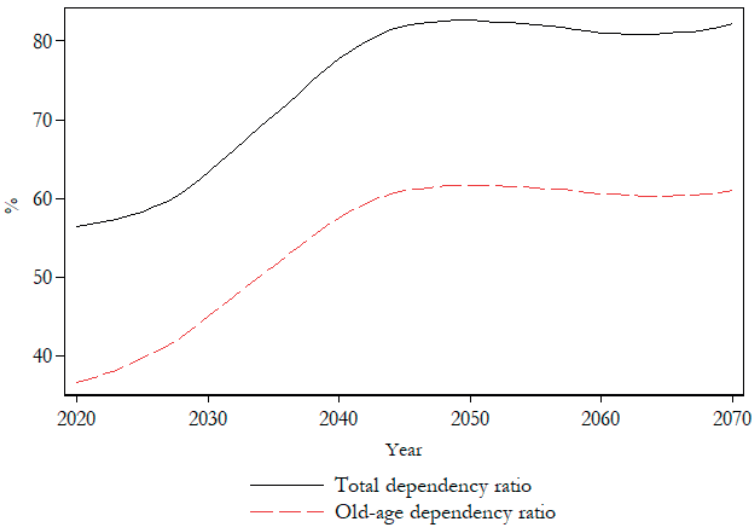
We shall first examine how the underlying sample of T-DYMM 3.0 evolves in its demographic structure.
In accordance with recent historical data and projections, the sample steadily shrinks over time in terms of individuals (Figure 3.1). By 2070, the sample has reduced by 11% compared to 2020, perfectly in line with Eurostat projected reduction for population numbers. In terms of households, in the first years of the simulation the increase in the propensity to divorce and the reduction in the propensity to form couples (see above Par. 2.1) observed in the recent data produce a slight increase in the number of units. When this process of "atomization" stops, the two dynamics for households and individuals embark on a similar pattern. By 2070, households will have increased by 1.6% compared to 2020.
The decrease in sample size is expectedly associated with a fast ageing of the sample. Figure 3.2 shows the dynamics of the dependency ratio and of the old-age dependency ratio, respectively computed as the number of people aged under 15 and over 64 (dependents) divided by the number of individuals aged 15-64 and over 64 on 15-64. In accordance with Eurostat projections, both dependency ratios are expected to increase significantly in the first 30 years of the simulation, then decrease slightly and stabilize.

Figure 3.1 Sample evolution, individuals and households



Source: T-DYMM 3.0 – Authors' elaborations

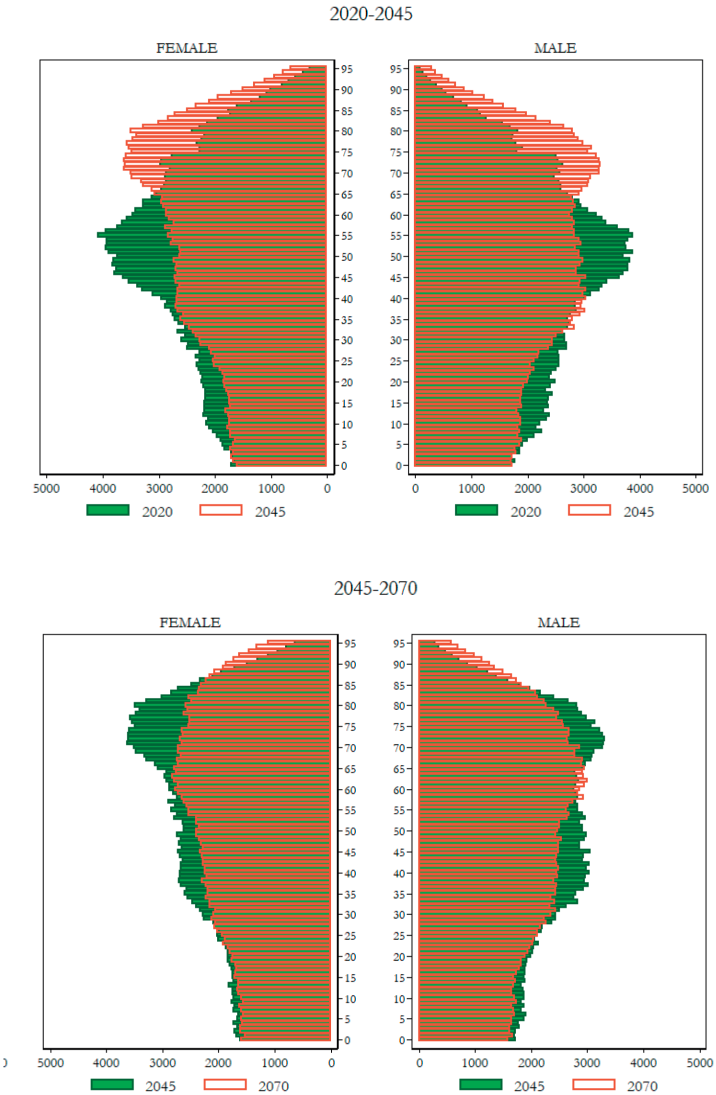
Figure 3.2 Dependency ratios



Source: T-DYMM 3.0 – Authors' elaborations

Figure 3.3 illustrates the evolution of the age composition in the sample by confronting population pyramids in 2020 and 2045 and then in 2045 and 2070. The same implications from Figure 3.2 can be derived here: the largest modifications in the age structure are expected to take place in the next 30 years.

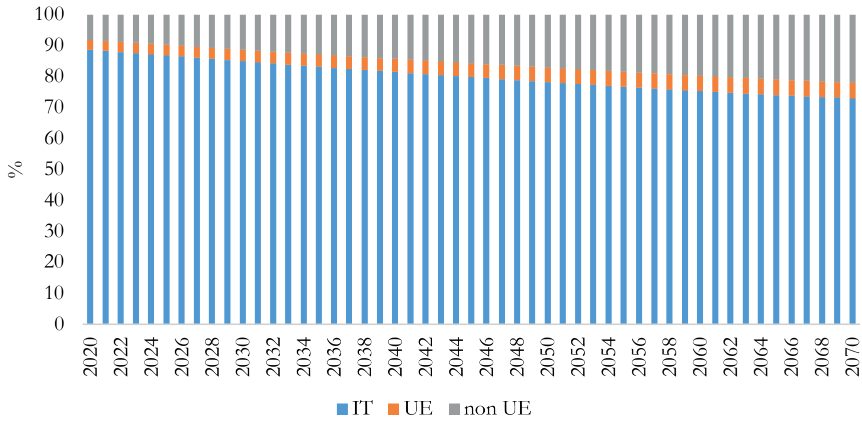
Figure 3.3 Populations pyramids by gender



Source: T-DYMM 3.0 – Authors' elaborations

In terms of the composition of the sample by area of origin, we have seen in Section 2.1 that, while overall inflows and outflows of migrants by age and gender are aligned to Eurostat projections, the distribution by area of origin after 2018 is kept constant by gender and age group according to the latest ISTAT data. Following these assumptions, each year in the 2020-2070 period around 72% of the immigrants (30% of the emigrants) were born in countries outside of the EU, 18% of the immigrants (15% of the emigrants) were born in foreign EU countries and 10% of the immigrants (55% of the emigrants) were born in Italy. As a result of these flows, while in 2020 90% of the sample was born in Italy, by 2070 that percentage would reduce to 73%. Figure 3.4 illustrates the evolution of the sample composition by area of birth over the simulation period.

Figure 3.4 Sample composition by area of birth (Italy, EU, non-EU)



Source: T-DYMM 3.0 – Authors' elaborations

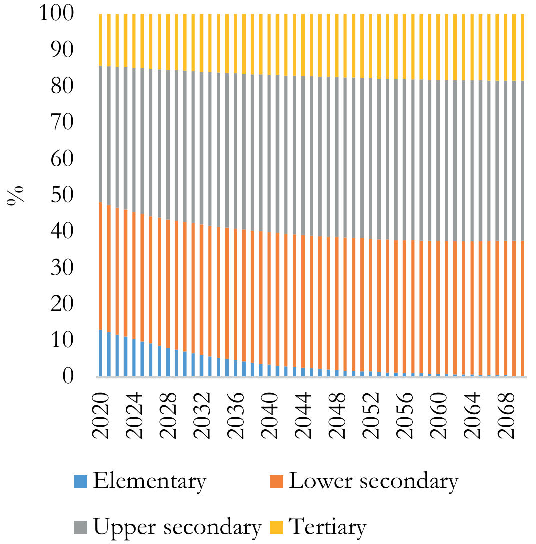
Figure 3.5 illustrates the evolution of educational levels for individuals aged over 30[1], by gender. Even though probabilities to get higher education are kept constant to those observed for 30-34 year-olds in the latest available data (see Section 2.1), education for younger cohorts is higher, therefore the portion of adults holding a higher educational degree increases over time, while people holding only elementary education nearly extinguish. Higher educational levels for females are both due to the higher propensity of young Italian-born women to get a university degree and to the lower educational levels of male immigrants[2].

1 29 is the latest age to get a higher educational degree in T-DYMM 3.0 (see Section 2.1).

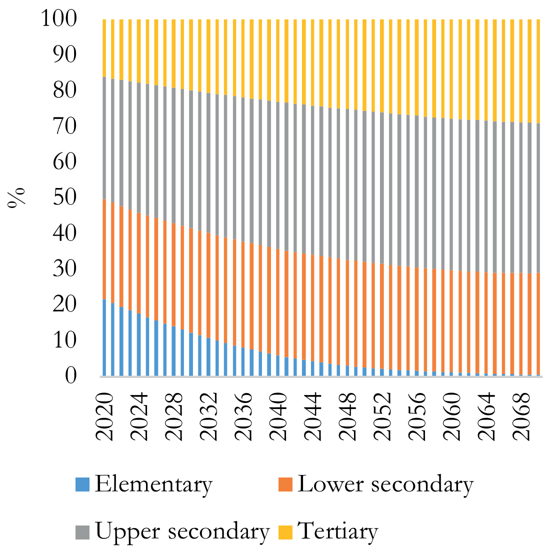
2 As illustrated in Section 2.1, for immigrant flows we assume that educational levels stay constant to OECD data relative to present stocks. We are considering different assumptions on the educational levels of future

Figure 3.5 Sample composition by educational achievement, over 30 years of age

a. Males



b. Females

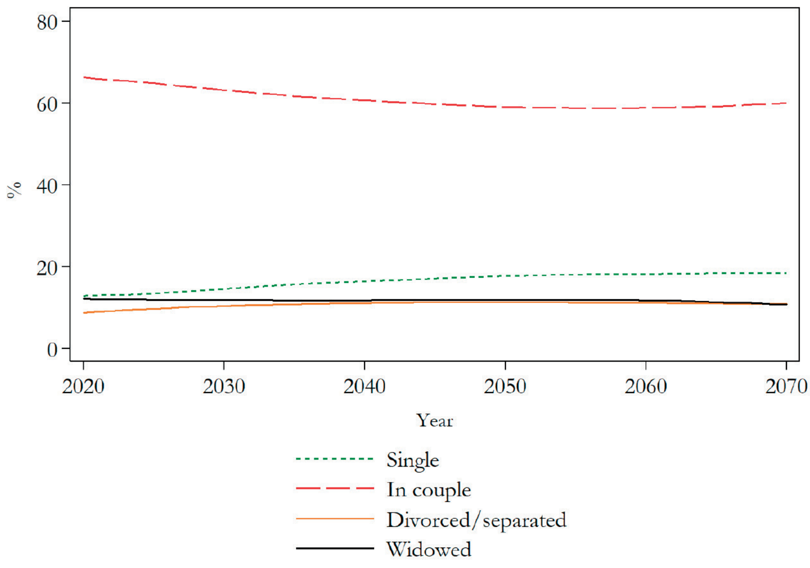


Source: T-DYMM 3.0 – Authors' elaborations

immigration flows for alternative scenarios.

Concerning household formation for young people, our methodology (illustrated in Section 2.1) makes it possible to keep the percentage of 18-34 year-olds still living in their original household (notoriously high in Italy) quite consistent over time, at about 60% for women and 70% for men, which is in line with the latest ISTAT data. Figure 3.6 illustrates the evolution of the sample by civil state for people aged 40 and over. In the first 20 years of the simulation, the increase in the propensity to divorce and the decrease in the propensity to form couples lower the quota of individuals in a couple by about 6 p.p., while the portion of singles increases. The "divorced/separated" component increases visibly until 2040, then stabilizes, in accordance with the assumptions illustrated in Section 2.1, while the "widowed" slightly but steadily decreases over time, as a consequence of both the reduction of coupled individuals and the equalization in life expectancy by gender. Amongst the "in couple" individuals, in 2020 90.5% of them are formally married; following a present propensity to favour informal unions, by 2070 this percentage would have steadily reduced to 78.9%.

Figure 3.6 Sample composition by civil status3, over 40 years of age



Source: T-DYMM 3.0 – Authors' elaborations

[3] The "in couple" category includes formal and informal marriage. The "divorced/separated" and "widowed" categories include individuals who have split (lost a partner) from a formal or informal marriage and have not formed a new couple. By exclusion, "single" individuals have never been in a formal or informal marriage.

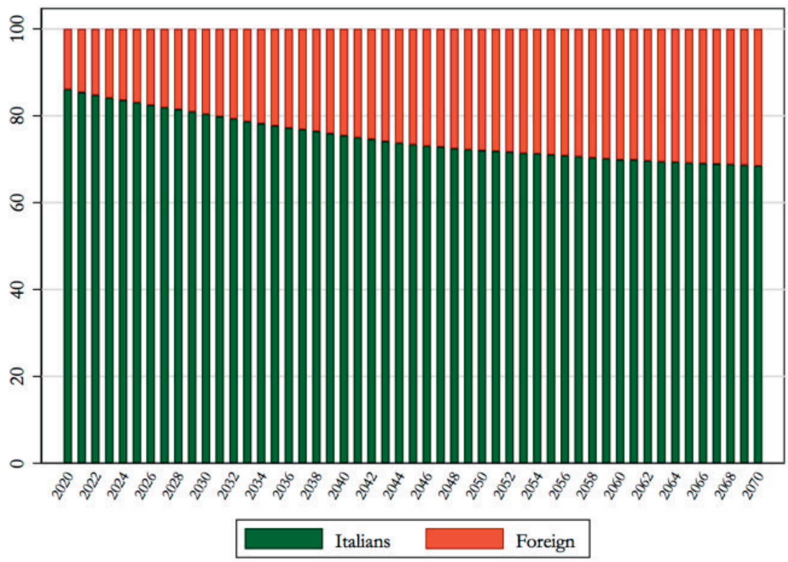
3.2 Labour Market Module

In this section we present projection results related to labour market outcomes from 2020 up to 2070. Aims of the section are to illustrate how the parameters concerning labour market transitions, earnings and months worked estimated on the AD-SILC dataset affect our sample of workers over time, especially in terms of area of birth, gender, age, education structures and employment category. Whenever relevant, we illustrate a separate analysis for working pensioners.

3.2.1 In work

Concerning overall employment, results follow the path traced by the alignment process related to employment rates by age and sex, as described in Section 1.2.
As a first aspect, we investigated the effects of demographic change on the labour market. Two main trends seem to be at play. On one hand, over time the Italian labour market faces the challenges of an ageing workforce. On the other hand, the immigrant workforce, relatively younger than the native one, accounts for a sizable part of employment, as shown in Figure 3.7. At the end of the period foreign workers who are employed represent about 30% of total employment.

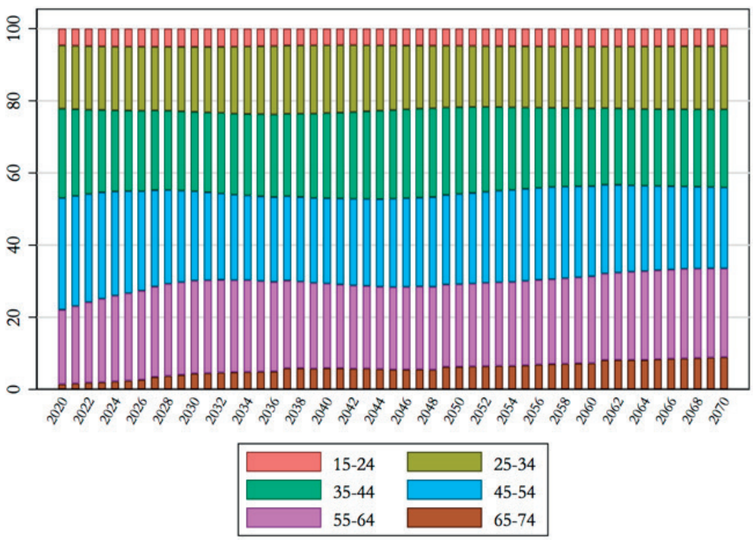
Figure 3.7 Immigrants in the Italian labour market



Source: T-DYMM 3.0 – Authors' elaborations

As a result, although there is growth in the immigrant component on the labour market, an ageing workforce will take place in the overall projection. The mean and the median employment age rise respectively from 44.9 and 46 in 2020 to 47 and 48 in 2070. Along the horizontal simulation period we observe rising shares of older workers (55 and over) compensated for by a decline in the share of middle-aged workers (35-54), (figure 3.8). The illustrated trend is similar for both genders.

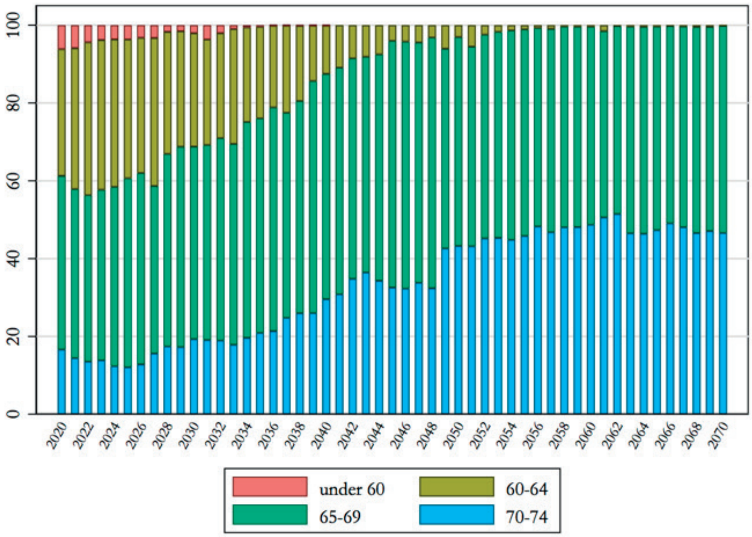
Figure 3.8 Composition of employment by age class



Source: T-DYMM 3.0 – Authors' elaborations

Turning to working pensioners, Figure 3.9 shows the distribution of the retired population in employment among different age classes. Clearly the pattern changes very quickly: mean and median age of working pensioners rise from 65.5 and 67 respectively in 2020 to 69.5 and 69 in 2070.

Figure 3.9 Retired population in employment by age class



Source: T-DYMM 3.0 – Authors' elaborations

3.2.2 Employment categories

A central issue in the labour market is related to the composition of employment by work category.

Concerning the employment categories simulated[4], only the share of public employee is aligned, as explained in Section 2.1. As a consequence, the relative share over total employment of each of the employment categories included in the model moves according to the individual coefficients estimated on AD-SILC data, as illustrated in Section 2.1.

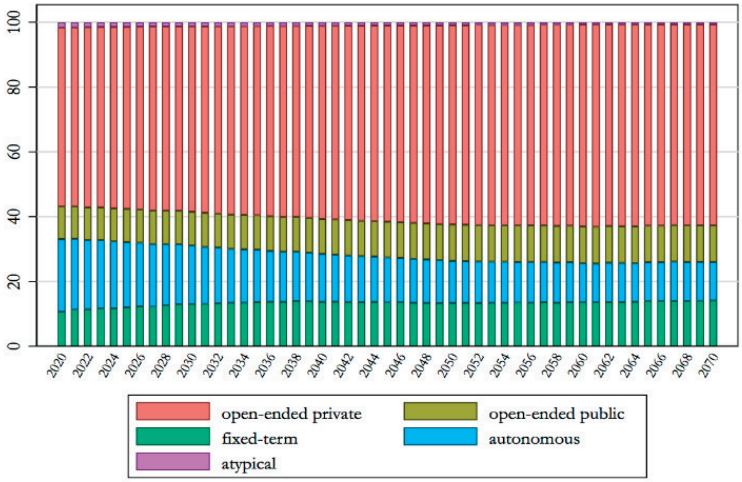
Figure 3.10 illustrates the distribution of work typologies over total non-retired employment for both men and women, over the entire projection period. By far the largest work category for both genders is represented by the employees with permanent contracts in the private sector. This category absorbs about 54% of total employment at the beginning of the simulation and grows by 10 p.p. over the projection horizon for women and by 7 p.p. for men. For the other categories, the ranking and the pattern

[4] Here we are not separating fixed-term employees by sector, because there are very few non-permanent employees in the civil service, especially male ones. In addition, we have grouped atypical and self-employed workers under the name of autonomous.

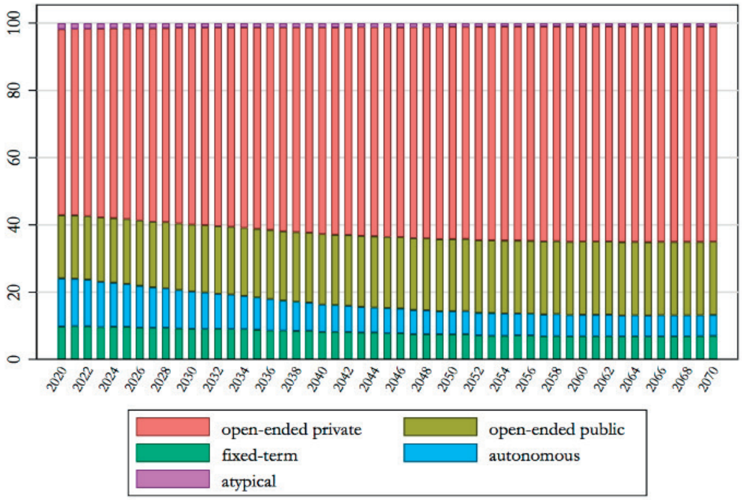
of evolution over time depend instead on the gender considered. For men, at the beginning of the simulation the self-employed represent 24% of the total share of employment, followed by public permanent employment and temporary employment, public and private (both at 10%) and, lastly, by atypical work (1.5%). However, the proportions among the categories are not constant over time. The share of self-employment declines by about 13 p.p. compensated for by an increasing share of both temporary and permanent private employees, while public employment remains quite stable over time (due to the alignment). For women, the second largest category is represented by public employment (18.5%) followed by self-employment (15.5%), temporary employment (10%) and atypical work (2%). Over the projection's horizon, on the one hand, the share of self-employed halves and a slight reduction of female temporary and atypical workers is observed. On the other hand, we observe an increase in permanent employment, both public and private.
Figures 3.11 and 3.12 illustrate for both men and women how the work typologies are distributed and how they evolve in time among the different age classes. The shares of private permanent employment increase over time for all age classes above 35, specifically at the age of 55 and above. Atypical contracts are instead concentrated in younger age classes, at the initial stage of the individual career, especially among women. Temporary occupation is not constant either over age nor between genders. For women, fixed-term contracts are concentrated among young cohorts, while for men we observe a rise in temporary employment also in older cohorts over the simulation period. At the same time, we observe a reduction in the share of self-employed, particularly true for men in older age cohorts. The public sector represents an important category for women after the age of 40 and for men after the age of 50.

Figure 3.10 Employment composition by category

a. Males



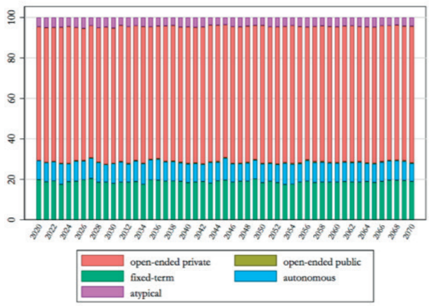
b. Females



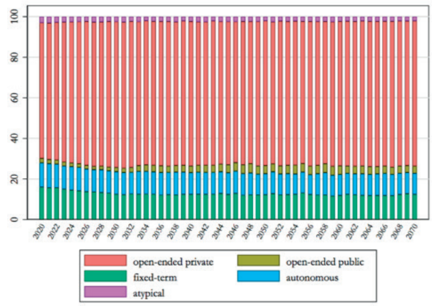
Source: T-DYMM 3.0 – Authors' elaborations

Figure 3.11 Employment composition by age class and work category. Females

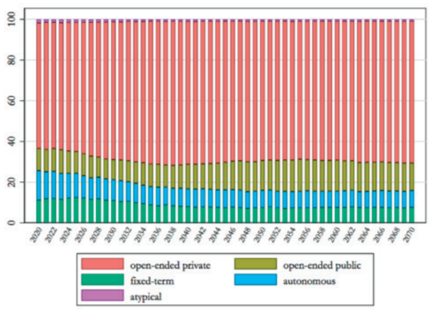
a. 15-24



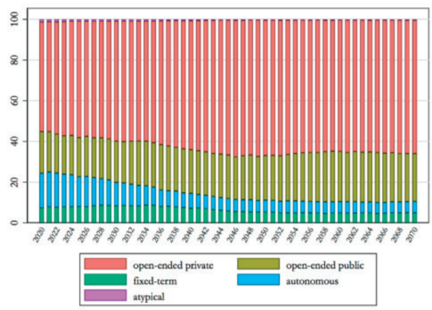
b. 25-34



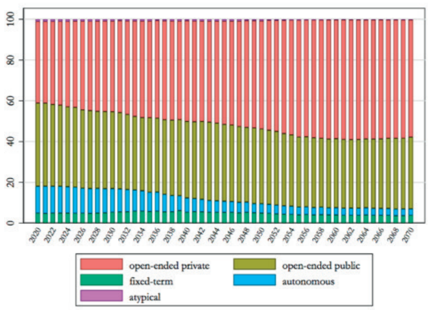
c. 35-44



d. 45-54



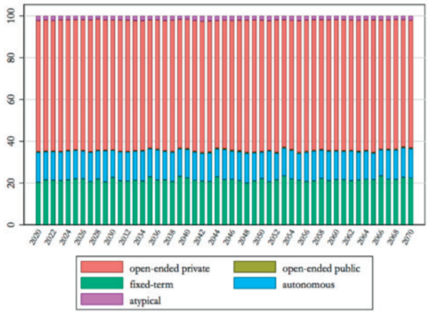
e. 55-69



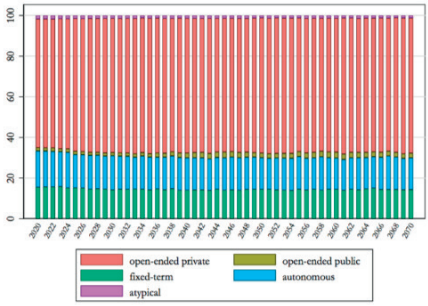
Source: T-DYMM 3.0 – Authors' elaborations

Figure 3.12 Employment composition by age class and work category. Males

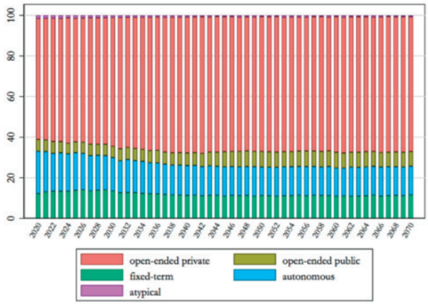
a. 15-24



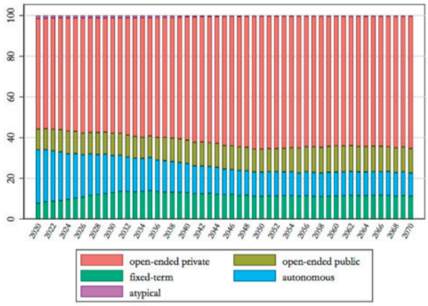
b. 25-34



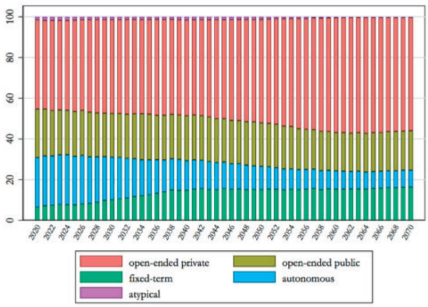
c. 35-44



d. 45-54



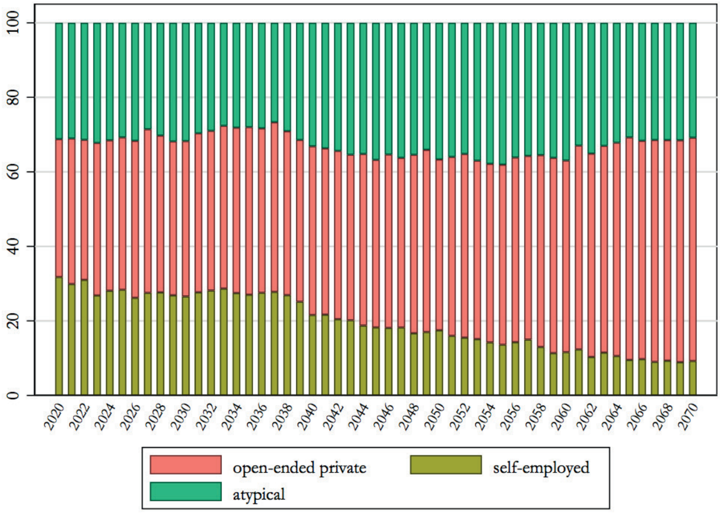
e. 55-69



Source: T-DYMM 3.0 – Authors' elaborations

Figure 3.13 shows the distribution of employment categories for working pensioners. Over the simulation period, we observe a change in the characteristics of retired people at work: the share of self-employed rapidly decreases and the share of permanent employees promptly rises. A slight increase in atypical contracts is also observed.

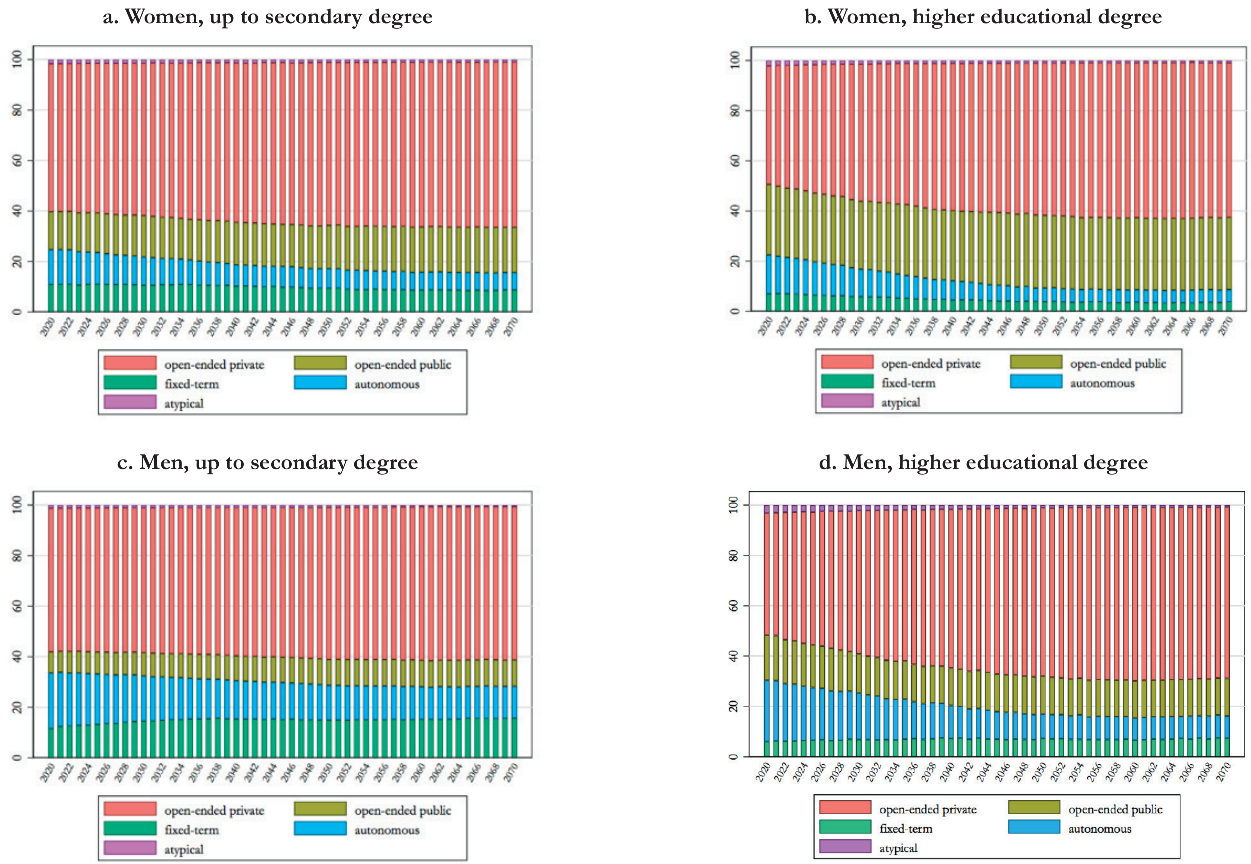
Figure 3.13 Working pensioners by employment category



Source: T-DYMM 3.0 – Authors' elaborations

We have also investigated the role played by educational level in the labour market. Interesting evidence is related to the comparison between gender and higher educational degree (Figure 3.14). For women, the higher educational degree is associated with a higher share of public employment and a lower share of temporary work. Throughout the simulations, the number of self-employed women decreases over time, and this is more evident for workers with a higher educational level. At the end of the projection, 90% of women with a higher educational degree work as permanent employees, both public and private. Self-employed, temporary and atypical workers represent a residual category. For men a similar pattern is observed but, in this case, the share of temporary employment grows over time, especially among less educated workers.

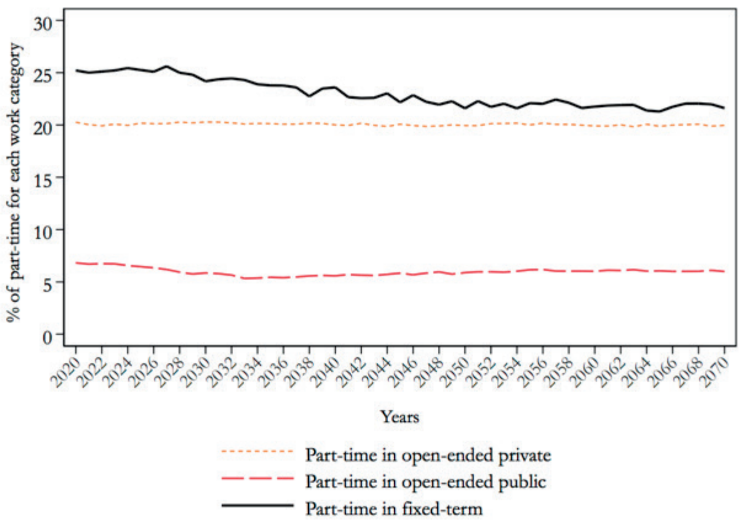
Figure 3.14 Educational level associated with employment category



Source: T-DYMM 3.0 – Authors' elaborations

Another relevant aspect concerns working time. Indeed, the literature frequently points to part-time workers as one of the causes of the "working poor" phenomenon, because the reduced number of working hours translates into low wages. Our data confirms that part-time workers are wildly spread throughout the private sector. The share of part-time over the total amount of employees (not retired) is illustrated in Figure 3.15. The percentage of part-time workers remains quite constant over time for permanent employees, and slightly decreases for temporary and public workers.

Figure 3.15 Part-time employees



Source: T-DYMM 3.0 – Authors' elaborations

3.2.3 Months and monthly wages

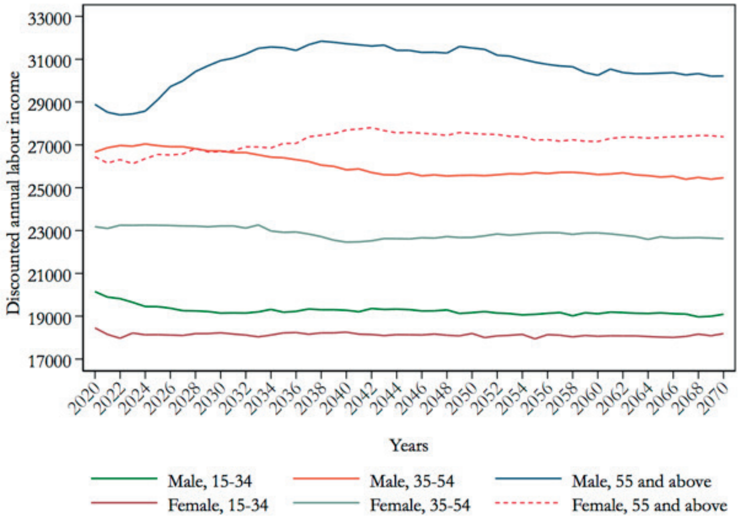
This section explores the dynamics of wages along the simulation exercise. In the simulation, labour incomes are indexed to labour productivity and ISTAT consumer price index, but results here are discounted to allow for an easier reading. In this section, we focus on full-time workers that have not retired yet. Figure 3.16 illustrates the evolution of median annual wages, by gender. As expected, a gender gap is observed and it remains quite constant over time. This effect can be investigated in depth paying attention to differences among age classes. In Figure 3.17, annual earnings by gender and age are shown. It is very clear here that the differences increase with age. If a limited gap is observed in the age class 15-34, quite constant over the simulation period, for the age above 35 the magnitude of the gap becomes relevant. For workers

above the age of 55, small differences are observed at the beginning of the projection, whereupon the differential increases over time and, in the last two decades of the simulation period the gender gap appears to decrease slightly.
Beyond gender differences, education plays again plays an important role in explaining wage differential. In particular, a wage premium is associated with a high educational attainment. This information can be driven by Figure 3.18. We observe a wage premium quite constant over the simulation period of about 10,000 euro per year for men and of about 6,000 for women.

Figure 3.16 Annual wages by gender. Median values

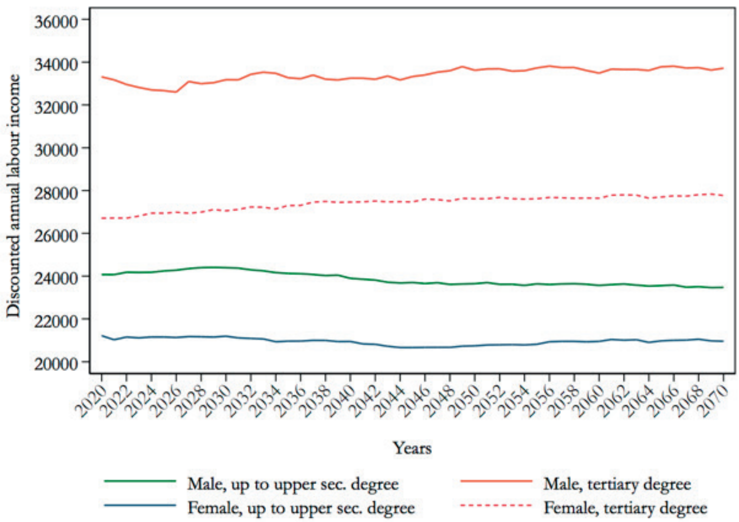
Source: T-DYMM 3.0 – Authors' elaborations

Figure 3.17 Annual wages by gender and age class. Median values



Source: T-DYMM 3.0 – Authors' elaborations

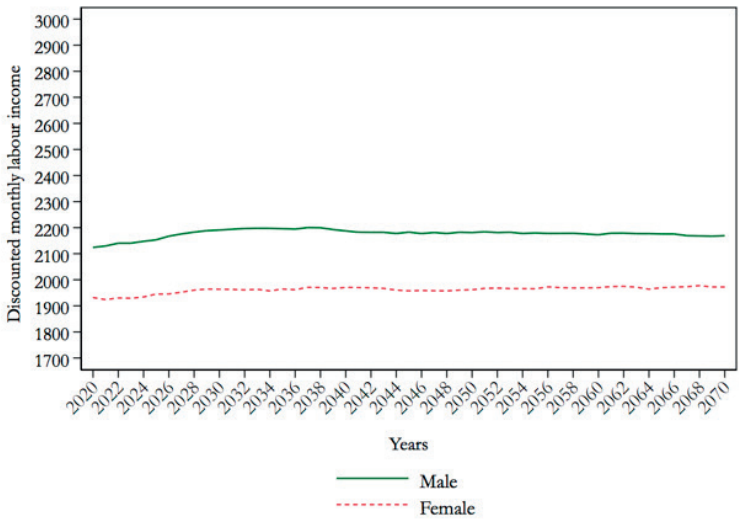
Figure 3.18 Annual earnings by gender and educational attainment. Median values



Source: T-DYMM 3.0 – Authors' elaborations

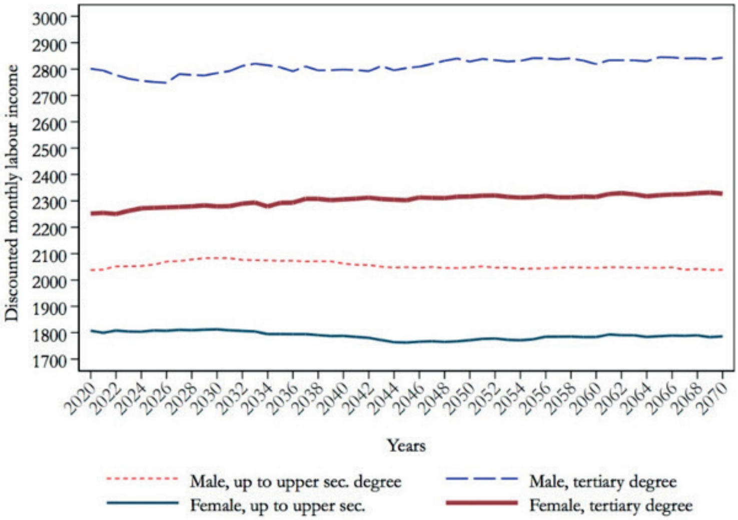
Differences in annual wages depend, of course, on the effect of twofold components: on the one hand, it depends on the monthly differences in earnings, and, on the other hand, on the effect of job duration, i.e. the number of months worked in the year. Considering the first aspect, Figure 3.19 illustrates income per month received by men and women working full time. The gap seems to exist, even if limited in its extension, and remains quite constant over the projection period. In particular, huge differences are observed if we explore the gap between men and women with a higher education, as in Figure 3.20. Here, we observe a strong difference between men and women with a higher educational degree and a limited gap for workers with an educational level up to secondary.

Figure 3.19 Monthly wages by gender. Median values



Source: T-DYMM 3.0 – Authors' elaborations

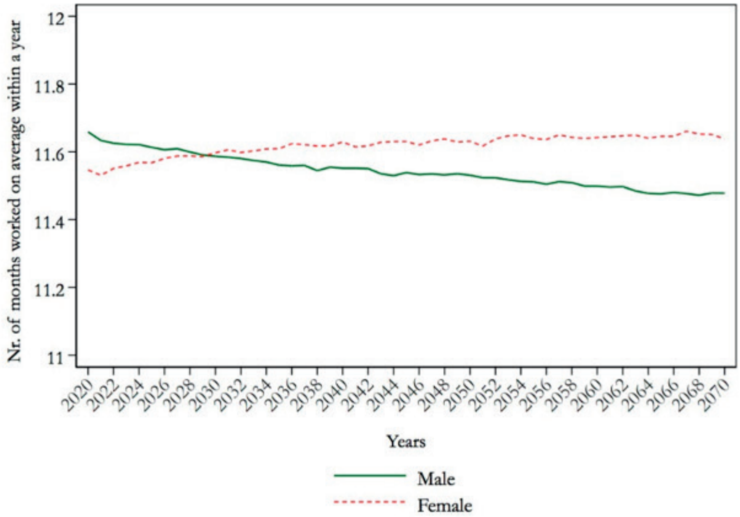
Figure 3.20 Monthly wages by gender and educational attainment. Median values



Source: T-DYMM 3.0 – Authors' elaborations

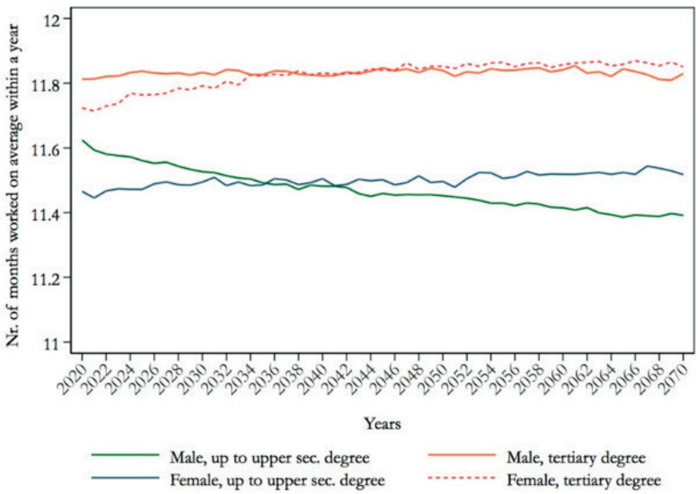
Considering the second aspect, i.e. job continuity, we use, as a proxy, the number of months worked, on average, by year (Figure 3.21). Here, for full-time workers, over the projection horizon an unexpected result is observed: it seems there are no significant differences between men and women. However, when looking at the educational attainment jointly with gender for employees (Figure 3.22) we observe a different result.

Figure 3.21 Number of months worked by an employee in a year by gender. Mean values



Source: T-DYMM 3.0 – Authors' elaborations

Figure 3.22 Number of months worked by an employee in a year by gender and educational attainment. Mean values



Source: T-DYMM 3.0 – Authors' elaborations

Workers with a higher educational degree, on average, are able to cover almost the entire year, with an overlapping and quite stable trend over the projection. A different result for workers without a higher educational degree is observed. In this case we observe fewer days worked, and the differential observed with respect to workers with a higher educational degree increases over time for men and remain constant among women.

3.3 Pension Module

In the present section, we shall focus on the results produced by T-DYMM 3.0 in its Pension Module.

3.3.1 Public pensions

Let us first explore the level of coverage of the pension system regarding the elderly. Figure 3.23 illustrates the percentage of individuals over 64 years of age who are recipients of: i) Old-age or seniority pensions; ii) Inability pensions; iii) Survivor pensions; iv) Any of the above.

For males, the most relevant change can be observed for old-age and seniority retirement: the quota of elderly males (over 64 years of age) that receive this type of pension benefit decreases by over 21 p.p. in the 2020-2070 period. That happens first of all because, across the simulation period, age requirements for retirement are updated according to changes in life expectancy, hence retirement ages will increase. Second, as observed in Section 3.1, the quota of migrant workers steadily increases throughout the simulation period. Since no microdata on pension rights for migrant workers is available to us, we assume that they do not hold any when they enter Italy. Hence, in our simulations, more commonly than for Italian-born workers, migrant workers may not meet retirement criteria and therefore have to rely on social assistance. Similar forces operate on the indicator for females; however, they are counterbalanced by increasing employment rates for the female workforce, so much so that, in 2070, the percentage of females over 64 years of age who are recipients of old-age or seniority pensions actually has increased by 2 p.p. compared to 2020. For elderly females, a strong reduction can be seen in the number of recipients of survivor pensions, due to both the reduction in the number of marriages and the equalization in life expectancy across genders observed in recent years. For both genders, a slight reduction in the number of recipients of inability pensions is seen (offset by a corresponding increase in the incidence of disability allowances, see Section 3.5).

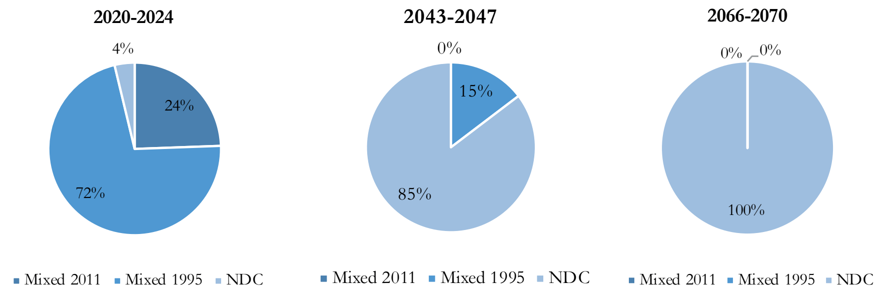
Figure 3.23 Coverage of the pension system for individuals aged 65 and over

Source: T-DYMM 3.0 – Authors' elaborations

Since the Italian pension system is still undergoing a pivotal change from a Defined Benefit to a Notional Defined Contribution scheme, we shall examine how the simulation sample evolves in terms of pension computation rules.

Figure 3.24 illustrates the proportions of newly retired individuals by pension regime (see Section 2.3 for a definition of the regimes in place in the current legislation). In the first years of the simulation, for the vast majority of new pensioners, benefits are computed following the old DB rules for a certain proportion. Throughout the simulation, that portion shrinks, and by 2070 all workers are fully enrolled in the NDC scheme.

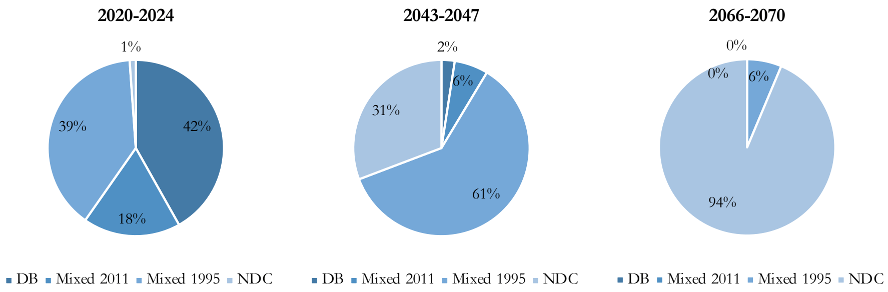
Figure 3.24 Newly retired pensioners by pension regime



Source: T-DYMM 3.0 – Authors' elaborations

If one looks at the overall number of pensioners, however, in the mid-years of the simulation (2043-2047) the vast majority of retirees belongs to either the DB or the Mixed category. Even in 2070, 75 years after the passing of the legislation that put the NDC scheme (Law 335/1995) in place, a portion of the pensions in payment would still be computed according to DB rules (Figure 3.25).

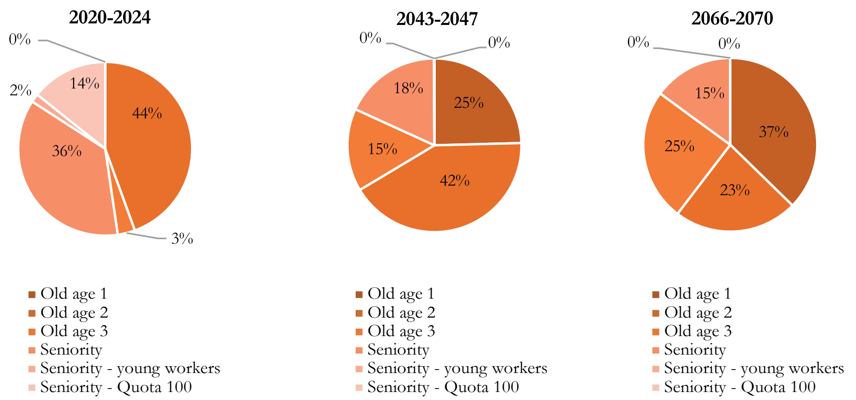
Figure 3.25 Overall number of pensioners by pension regime



Source: T-DYMM 3.0 – Authors' elaborations

Looking at retirement criteria (Figure 3.26), in the first years of the simulation most workers are accessing retirement through "Seniority" channels[5]. "Seniority - young workers" is not accessible to NDC workers and "Seniority - Quota 100" is set to be discontinued after 2021, therefore the two criteria are not in use after the first years of the simulation. On the other hand, "Old age 1", a type of early retirement for workers who have enjoyed fruitful and/or long careers[6], and "Old age 3", a "last resort" type of retirement for workers with very short careers[7], are both only accessible to NDC workers and gain progressively more importance.

Figure 3.26 Newly retired pensioners by retirement criterion

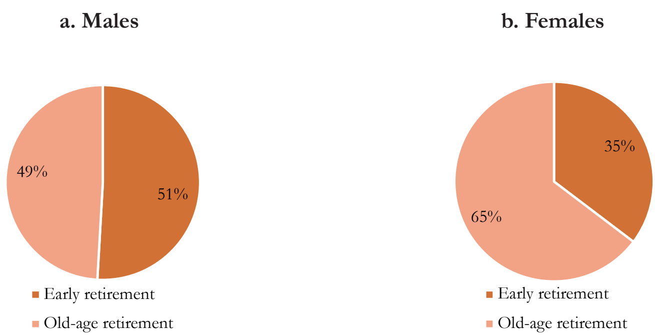


Source: T-DYMM 3.0 – Authors' elaborations

If we differentiate by gender, across the simulation period male workers are consistently more likely to satisfy early retirement criteria[8] (see Figure 3.27), as they generally enjoy steadier and better remunerated career jobs.

5 See Section 2.3 for a proposed classification of the different retirement criteria in the Italian pension system.
6 In order to access retirement, the resulting pension benefit has to be at least equal to 2.8 times the level of the social allowance for the elderly, the so-called *assegno sociale* (see Section 2.3).
7 Only 5 years of accrued contribution are required, while 20 are needed for "Old age 1" and "Old age 2" criteria.
8 This includes all "Seniority" criteria and "Old age 1".

Figure 3.27 Newly retired pensioners by retirement criteria and gender, 2020-2070

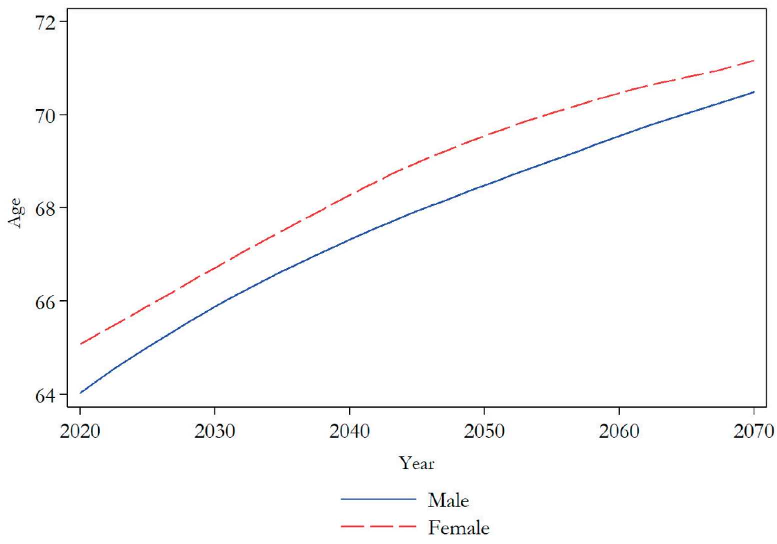


Source: T-DYMM 3.0 – Authors' elaborations

As a result of these discrepancies in access to retirement, in turn due to discrepancies within the labour market, average retirement ages for women are slightly higher than for men throughout the simulation period (even though the requirement in years of contribution for the "Seniority" criterion is one year lower for women than for men, see Section 2.3)[9]. Indeed, because women have a harder time meeting requirements for retirement, the likelihood of female workers accessing retirement through the "last resort", "Old age 3" criteria is nearly twice that of their male counterparts. According to T-DYMM 3.0 simulations, average retirement ages increase by four years for both genders (Figure 3.28) in the 2020-2070 period.

[9] According to the latest annual report from INPS, average retirement ages for men and women were both equal to 64 in 2019. In T-DYMM 3.0, in 2019 the average retirement age for women is about 9 months higher than for men. This is due to differences between the starting sample and the Italian population that cannot be fully corrected by our calibration procedure, and by the fact that, albeit rather complex, our model is still a simplification of the Italian legislation on pensions (we do not simulate *opzione donna*, which certainly lowers the average retirement age for women) and of individual behaviour.

Figure 3.28 Average age at retirement by gender

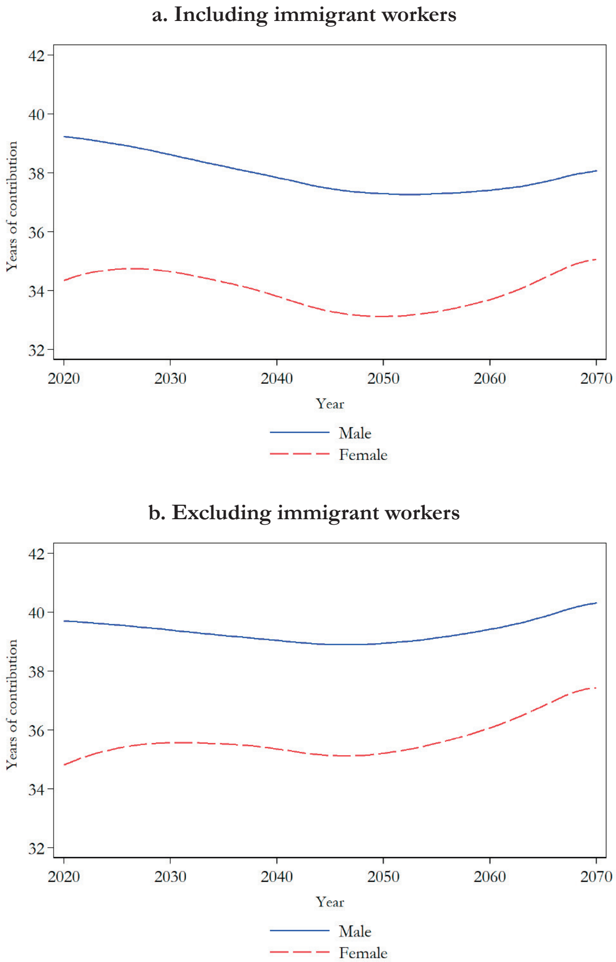


Note: lowess smoothing.
Source: T-DYMM 3.0 – Authors' elaborations

Despite visible increases in retirement ages for both genders, average years of contribution at retirement slightly decrease in the first years of the simulation, then recover (Figure 3.29). This is essentially due to: i) the maturation of workers born in the 1970s and early 1980s, who have more harshly experienced the effects of the long-lasting economic crisis following 2009 and ii) the (increasingly relevant) impact of immigrant workers, who often spend only a portion of their careers in Italy, but do not carry over any pension rights when they immigrate in our simulations[10]. If immigrant workers are excluded from the computations, average years of contribution at retirement stay roughly constant until the mid-2040s and then increase, especially for women. However, average years of contribution at retirement are still lower compared to their male colleagues at the end of the simulation period.

[10] See Section 2.1.

Figure 3.29 Average years of contribution at retirement by gender



Note: lowess smoothing.
Source: T-DYMM 3.0 – Authors' elaborations

As a result of the rapid increase in age requirements for retirement for female workers (until full equality was reached in 2018) and of the increase in average retirement ages due to the emergence of the "Old age 3" criterion for NDC workers (more widely-used by females than males), the gender differential in retirement duration decreases significantly throughout the simulation period (Figure 3.30). After about 15 years of slight increases in average years spent in retirement, the alignment of age requirements for retirement to life expectancy and the gradual extinction of the so-called "baby pensioners" inverts the trend. Starting from 2050, retirement duration stabilizes at around 22 years for women and 20 for men.

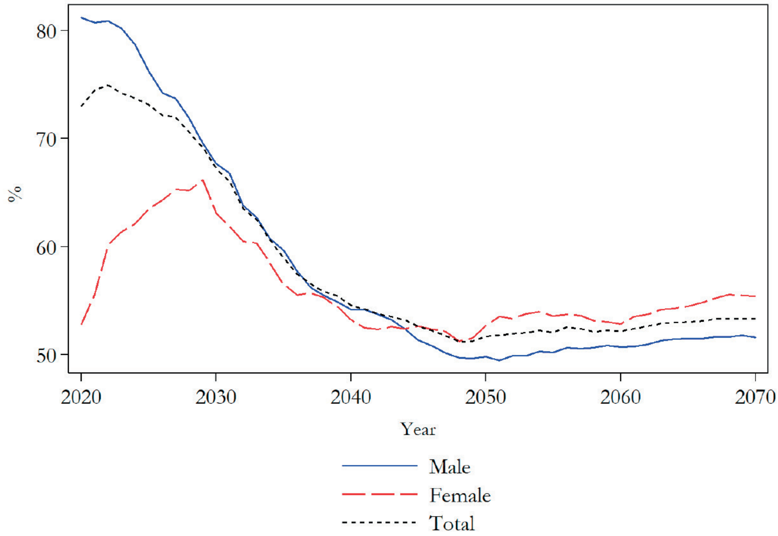
Figure 3.30 Retirement duration by gender

Source: T-DYMM 3.0 – Authors' elaborations

In line with recent trends, the Aggregate Replacement Ratio (ARR)[11] is steady in the first years of the simulation, then decreases and stabilizes at a little over 50% after 2050 (Figure 3.31). If one differentiates by gender, dynamics are opposite in the first 10 years of the simulation: women are still less protected by the pension system than men are, but are projected to recover by 2030 (in terms of ARR).

[11] The ARR is the ratio of the gross median individual pension income of the population aged 65–74 relative to the gross median individual labour income of the population aged 50–59, excluding other social benefits. It takes into account old-age/seniority, inability and survivor pensions.

Figure 3.31 Aggregate Replacement Ratio by gender

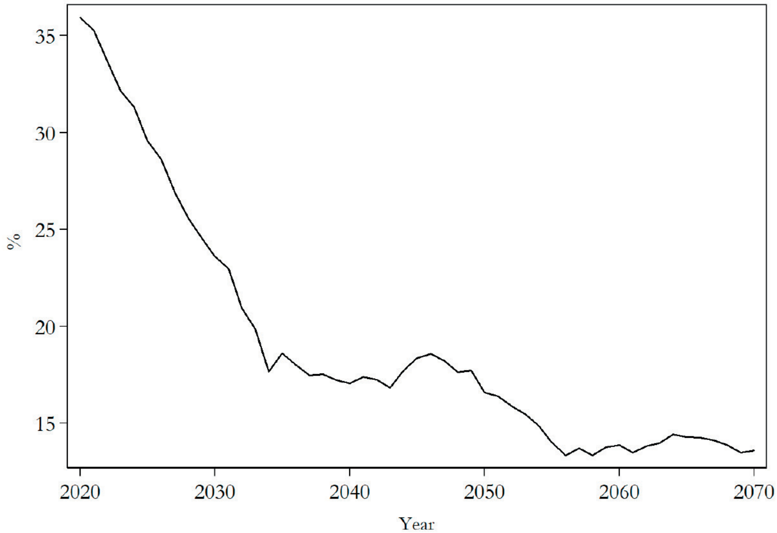


Source: T-DYMM 3.0 – Authors' elaborations

The Gender Gap in Pensions (GGP)[12] decreases sharply until the early 2030s, stays at around 17% until the late 2040s and decreases further by about 5 p.p. before stabilising at 14% in 2060 (Figure 3.32). On the one hand, fast-growing employment rates for women are a push for equalization, on the other, the disadvantaged position of women in the labour market in the past and present is reflected in future dynamics by means of our estimations on AD-SILC (discussed in Section 2.2), and that impedes going beyond a certain inequality threshold.

[12] The GGP is calculated for persons aged 65-79 as: $100 * (1 - \frac{average\ pension\ for\ females}{average\ pension\ for\ males})$. It takes into account old-age/seniority, inability and survivor pensions.

Figure 3.32 Gender Gap in Pensions

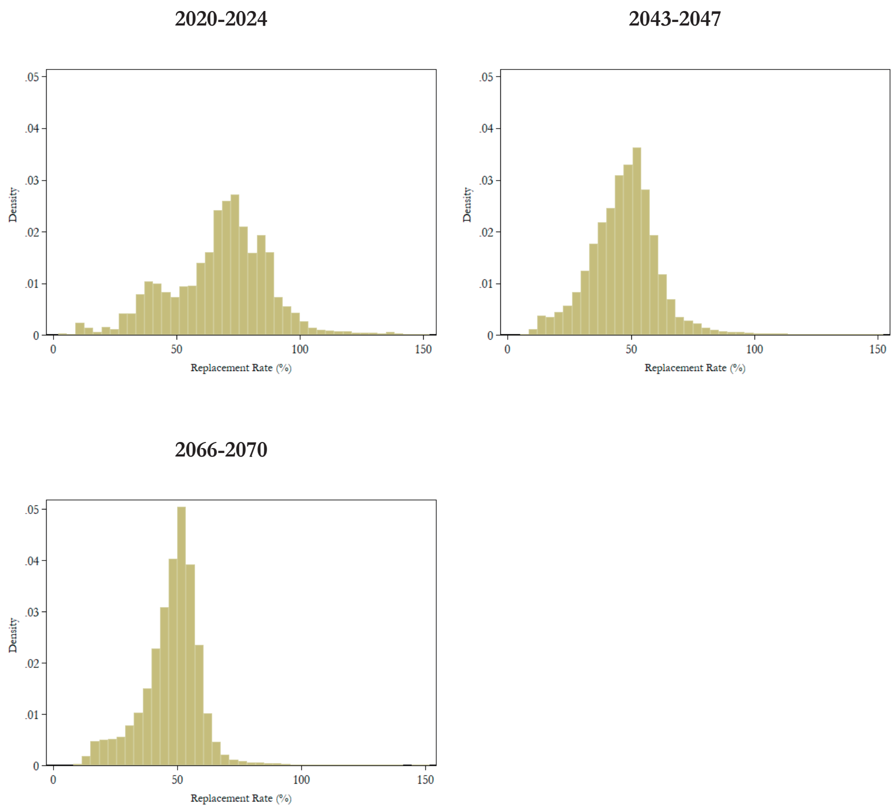


Source: T-DYMM 3.0 – Authors' elaborations

In order to compare individual positions at retirement throughout the simulation period we have calculated two indicators: i) a replacement rate, calculated as the percentage ratio between the first pension benefit and the average of the last five labour incomes (a subjective indicator); ii) the percentage ratio between the first pension benefit and the so-called "minimum amount" (*trattamento minimo*)[13] (an objective indicator). Figures 3.33 and 3.34 show how throughout the simulation period both indicators concentrate more, and around lower values.

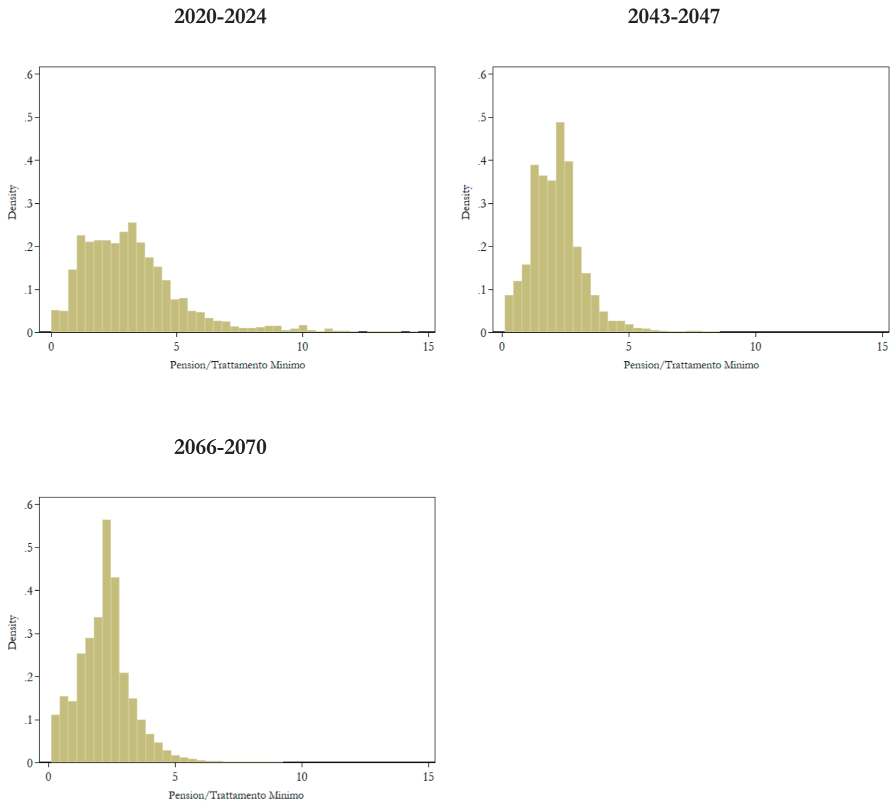
[13] See Section 2.3. The *trattamento minimo* amounted to € 515 a month in 2020.

Figure 3.33 Density of replacement rate values



Source: T-DYMM 3.0 – Authors' elaborations

Figure 3.34 Density of pension/*trattamento minimo* ratio values



Source: T-DYMM 3.0 – Authors' elaborations

NDC computation rules ensure actuarial neutrality: all contributors earn the same internal rate of return on accrued contribution, while old DB rules favour short and fast-growing careers, often associated with high-earning workers. Indeed, the transition from DB to NDC computation rules is expected to lower average benefits but also lower inequalities among pensioners, as richer workers should be the ones most impacted. Tables 3.1 illustrates the condition at retirement by birth cohort (five-year birth cohorts, from 1960 to 1989) in terms of average age on the one hand, median replacement rate and pension/*trattamento minimo* ratio on the other. The position of younger cohorts worsens in terms of both pension level and average age at retirement. As already mentioned, results are somewhat affected by the necessary assumption (due to lack of data) that migrant workers do not carry over any pension rights, which could prove overly pessimistic. If migrant workers were excluded from the computations, the average retirement age for the 1985-1989 cohort would be almost a year lower and the average pension at retirement about 5% higher.

Table 3.1 Condition at retirement by birth cohort

Birth cohort	Age *	Gross replacement rate **	Gross pension/ *trattamento minimo* **
1960-1964	66.7	65.3	2.5
1965-1969	67.3	59.4	2.2
1970-1974	67.8	53.6	2.3
1975-1979	68.6	48.0	2.1
1980-1984	69.1	47.8	2.2
1985-1989	69.7	47.4	2.2

Nota: * mean; ** median.
Source: T-DYMM 3.0 – Authors' elaborations

Table 3.2 illustrates the condition at retirement by birth cohort for the two poorest and the two richest income quintiles. It is apparent how the latter are more affected in terms of reduction in pension amounts. However, poorer workers will have a harder time meeting pension requirements, hence average retirement ages for them increase more significantly.

Table 3.2 Condition at retirement by birth cohort and income quintile

a. First and second income quintile

Birth cohort	Age *	Gross replacement rate **	Gross pension/ *trattamento minimo* **
1960-1964	68.2	49.9	1.4
1965-1969	68.6	47.8	1.4
1970-1974	69.4	44.2	1.5
1975-1979	70.3	41.8	1.5
1980-1984	70.9	42.2	1.5
1985-1989	71.6	41.2	1.5

b. Fourth and fifth income quintile

Birth cohort	Age *	Gross replacement rate **	Gross pension/ *trattamento minimo* **
1960-1964	66.0	69.0	3.2
1965-1969	66.5	63.4	2.8
1970-1974	66.9	56.7	2.6
1975-1979	67.5	50.4	2.4
1980-1984	68.0	49.5	2.5
1985-1989	68.6	49.3	2.4

Nota: * mean; ** median.
Source: T-DYMM 3.0 – Authors' elaborations

If we focus on "non-standard" workers (Table 3.3), here identified as individuals who have spent more than half of their careers as either fixed-term employees or "para-subordinate" (atypical) workers[14], throughout the simulation period their presence becomes more and more common: in the 2020-2024 "non-standard" workers constitute 1.4% of new pensioners; in 2066-2070, that percentage has gone up to 3.5%. Hence, while for the 1960s generation non-standard careers are generally associated with longer spells of unemployment and very low pensions, for people born in the 1980s they are much more common, though in retirement they still fare considerably worse than their cohort peers (see Table 3.1).

Table 3.3 Condition at retirement by birth cohort for "non-standard" careers

Birth cohort	Age *	Years of contribution *	Gross replacement rate **	Gross pension/ *trattamento minimo* **
1960-1964	69.0	28.8	35.1	1.1
1965-1969	69.5	27.4	38.3	1.3
1970-1974	69.7	29.9	41.2	1.5
1975-1979	70.5	28.0	40.2	1.4
1980-1984	70.6	30.2	42.6	1.7
1985-1989	70.4	32.3	43.0	1.8

Nota: * mean; ** median.
Source: T-DYMM 3.0 – Authors' elaborations

3.3.2 Private pensions

Amongst new pensioners, throughout the simulation period almost 69% of the males have a private pension, while the percentage is 60.3% for women. Expectedly, only 17% of new pensioners in the lowest or second-to-lowest income quintile have access to a private pension. Workers who have enjoyed longer, more stable careers seem to be benefiting the most from the chance to enrol in private pension plans. Table 3.4 illustrates the differences in the condition at retirement by birth cohort and career length, dividing workers between two classes: those who have accrued at least 40 years of contribution and those who have accrued less than 30[15].

[14] See Section 2.2 for a taxonomy of employment categories in T-DYMM 3.0.

[15] It should not come as a surprise that the average retirement age is higher for the latter than the former, as individuals who have accrued less years of contribution will have a harder time meeting pension requirements and therefore often access retirement through the "Old age 3" criterion (see Section 2.3).

Table 3.4 Condition at retirement by birth cohort and career length

a. Long careers (at least 40 years of accrued contribution)

Birth cohort	Age*	Gross replacement rate **	Gross replacement rate, including private pensions **	Gross pension/ *trattamento minimo* **	Gross pension, including private pensions/ *trattamento minimo* **
1960-1964	64.6	73.2	77.8	3.3	3.5
1965-1969	65.1	68.2	73.2	2.9	3.1
1970-1974	65.7	62.2	68.1	2.7	3.0
1975-1979	66.2	56.3	62.4	2.5	2.8
1980-1984	66.7	52.9	58.3	2.5	2.7
1985-1989	67.5	52.7	57.3	2.5	2.6

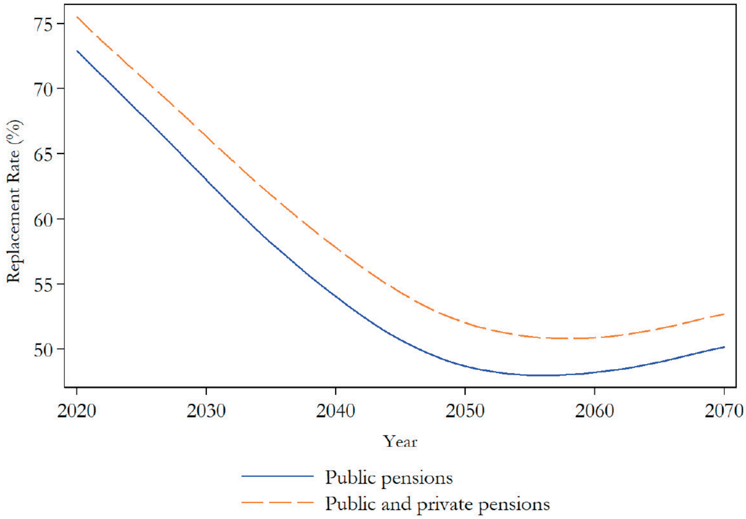
b. Short careers (less than 30 years of accrued contribution)

Birth cohort	Age*	Gross replacement rate **	Gross replacement rate. including private pensions **	Gross pension/ *trattamento minimo* **	Gross pension. including private pensions/ *trattamento minimo* **
1960-1964	69.6	36.6	37.7	1.1	1.2
1965-1969	70.5	35.9	37.0	1.2	1.2
1970-1974	71.0	34.3	35.3	1.2	1.2
1975-1979	72.0	33.9	34.9	1.2	1.2
1980-1984	73.0	32.5	33.2	1.0	1.0
1985-1989	73.6	33.1	33.8	1.0	1.0

Nota: * mean; ** median.
Source: T-DYMM 3.0 – Authors' elaborations

As a result of our assumptions on participation rates in private pension pillars (they are kept constant to 2020 values, see Section 2.3), private pensions have a limited effect on overall pension levels: Figure 3.35 presents the evolution of the replacement rates across the simulation period.

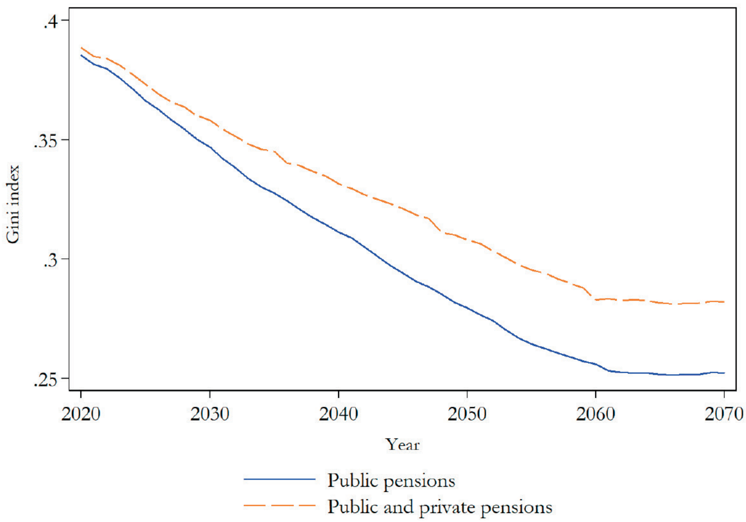
Figure 3.35 Replacement rate at retirement, public and private pensions



Note: Lowess smoothing on median values.
Source: T-DYMM 3.0 – Authors' elaborations

However, the regressive nature of the system of private pillars is evident if one looks at the evolution of inequality indicators (Figure 3.36). The equalization (around a lower average public pension) brought about by the NDC rules is reduced by private pension schemes.

Figure 3.36 Gini index on stock of old-age and seniority pensioners, public and private pensions



Source: T-DYMM 3.0 – Authors' elaborations

3.3.3 "Choice" scenario

As mentioned in Paragraph 2.3, in the Baseline scenario of T-DYMM 3.0 presented here all workers access retirement as soon as they meet requirements. While such an assumption seems acceptable at present, it may not seem so in the future, when the NDC transition is complete. While we are working on the implementation of a behavioural function to simulate retirement decisions, we propose in our Choice scenario[16] a first assessment of the effect of postponing retirement to increase one's pension benefit.

Across the simulation period, over 19% of workers who meet pension requirements choose to wait at least one year before retiring[17]. Expectedly, in the beginning of the simulation period this percentage is in the single digits, but it grows gradually and stabilises around 20% in the mid-2030s, when the transition to the NDC scheme has been completed. The possibility of exercising a "choice" is expectedly not evenly distributed. Throughout the simulation, almost 23% of male workers take advantage of the "choice" option, 15% of female workers. A total of 62% belong to the highest

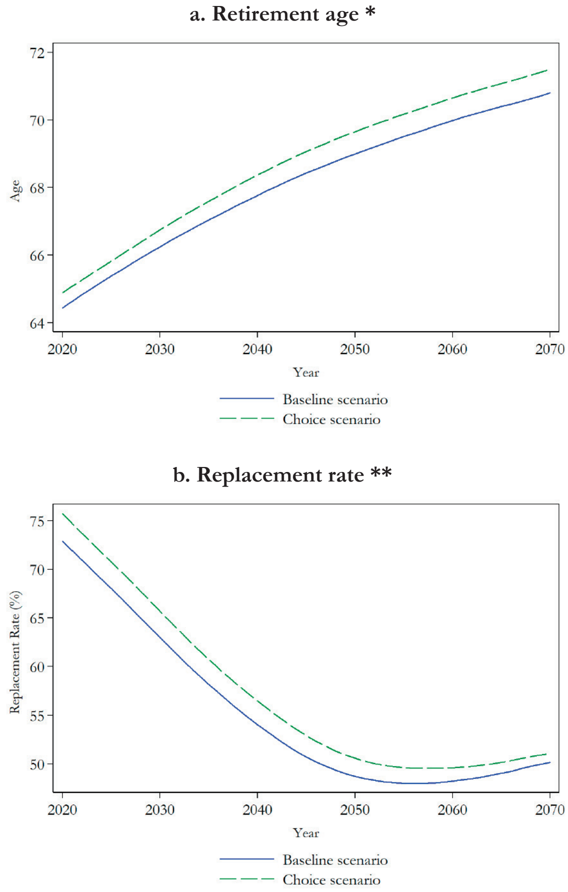
[16] See Section 2.3 for a description of the assumptions underlying the Choice scenario.

[17] The rest retire right away, either because they are legally obliged, they satisfy the replacement rate threshold set in place or have reached the maximum age limit.

income quintile, 82% are either in the fourth of fifth income quintile, while only a little over 10% of retiring non-standard workers (who have spent more than half of their careers as either fixed-term employees or atypical workers) have a chance to take advantage of the "choice" option. Steadier, better-remunerated workers are advantaged not just in the level of pension benefit they can ultimately enjoy, but also in the freedom to choose the profile that best suits them in terms of the balance between duration of retirement and level of pension.

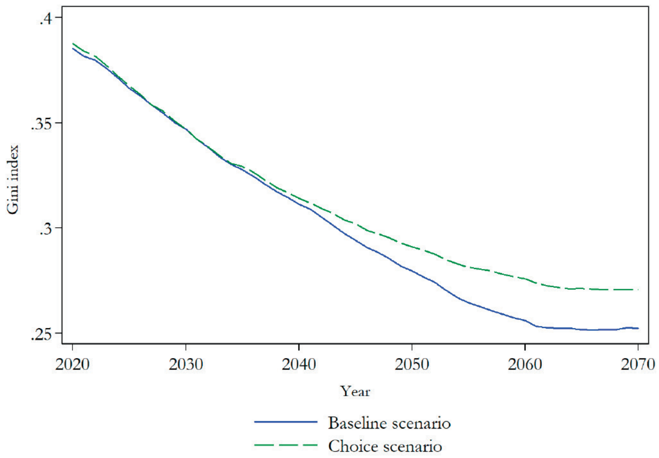
While the average impact of the Choice scenario on pension levels and average retirement ages is small (Figure 3.37), the effect on inequality indicators is visible (Figure 3.38).

Figure 3.37 Condition at retirement, Baseline and Choice scenarios



Note: Lowess smoothing; *mean; **median.
Source: T-DYMM 3.0 – Authors' elaborations

Figure 3.38 Gini index on the overall number of old-age and seniority pensioners, Baseline and Choice scenarios



Source: T-DYMM 3.0 – Authors' elaborations

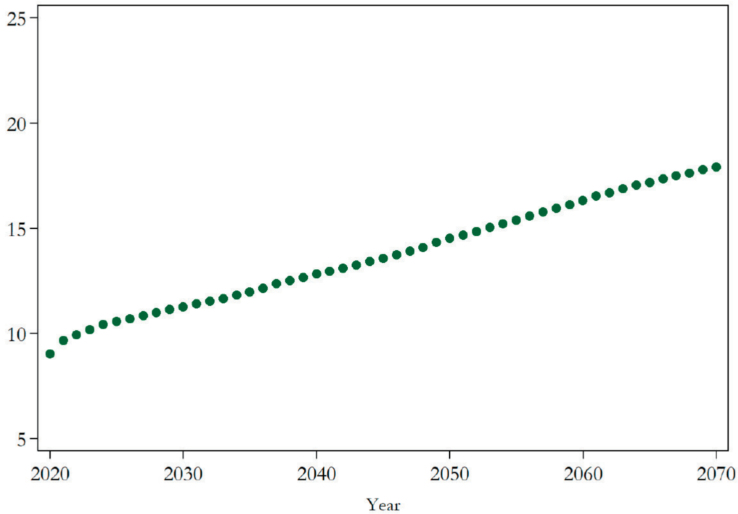
3.4 Wealth Module

The results of the simulation regarding wealth dynamics and inequality are presented at the household level. Therefore, these results are co-influenced by the evolution of the demographic and labour modules and should be read jointly with the results of those other modules.

Dynamic microsimulation models endowed with a wealth module allow a more comprehensive analysis of distributional dynamics, especially in a long-term intergenerational perspective. In this report, we carry out analyses on net wealth figures defined as the sum of real and financial wealth, net of liabilities.

Italy is one of the countries with the highest wealth-to-income ratio in the developed world, it was equal to 9.3 in 2017 (see Caprara *et al.* 2018). Moreover, this ratio has been rising in the last decades. Therefore, the evidence from the first simulation from the wealth module regards the increasing role of wealth in the next years. As we can see from Figure 3.39, the projected wealth-to-income ratio doubles from 9.0 in 2020 to 17.9 in 2070. This result is explained by the accumulation of wealth due to the savings effect related to the structure of the propensity to consume beyond one's current disposable income. The related savings rate is assumed to be invariant to institutional changes, and throughout the simulation period it is kept almost constant (on average but not in its distribution) to its current average national level, around 9%.

Figure 3.39 Wealth-to-income ratio

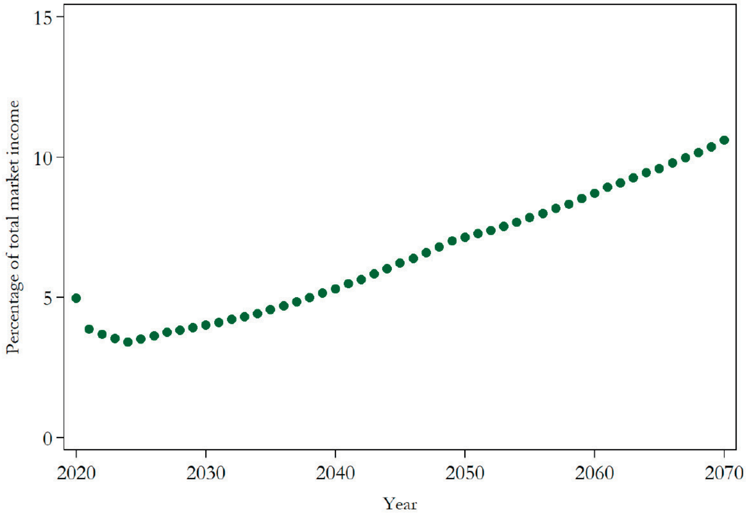


Source: T-DYMM 3.0 – Authors' elaborations

Some related evidence is that proposed in Figure 3.40. In the long-term, due to the wealth accrued in the model, the weight of capital income over total market income increases. This result is driven by the positive gap between the growth of wealth and that of salaries and pensions (an average of 1.5% in the projected years 2020-2070). Furthermore, the simplifying hypothesis of nil volatility on return rates among investors over time ensures a steady capital income share growth.

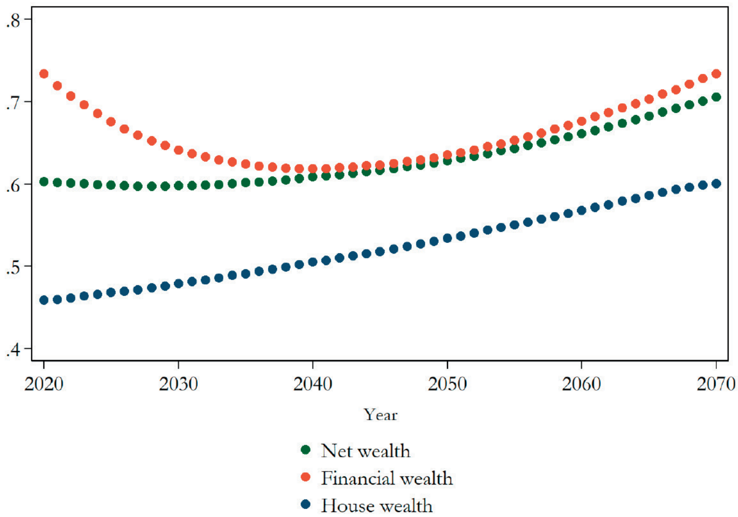
We shall now turn our focus onto the level of projected wealth inequality, measured by the Gini Index. From Figure 3.41, an overall increase in the Gini index is projected for net wealth in the simulation period from 0.6 in 2020 to 0.7 in 2070 (green dots). This result is coherent with what was found by Tedeschi *et al.* (2013). In their work a long-term increasing trend in wealth inequality emerges when a reduced-form consumption rule is adopted (as the one used in this version of the model, see Section 2.4).

Figure 3.40 Gross capital income on Total market income ratio



Source: T-DYMM 3.0 – Authors' elaborations

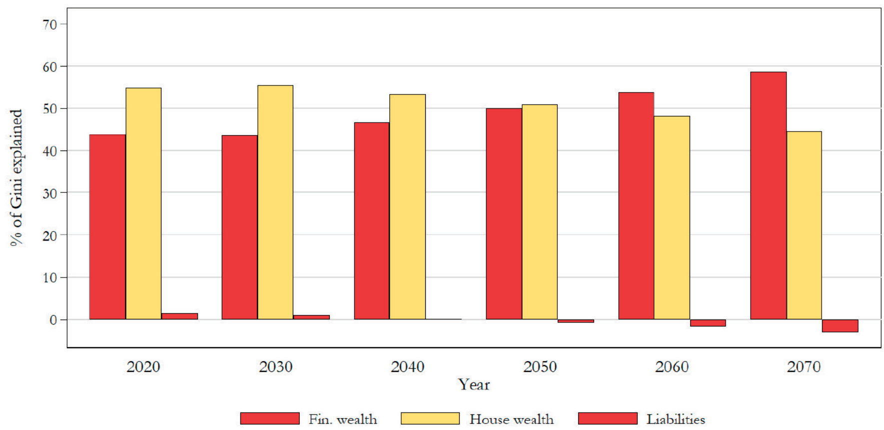
Figure 3.41 Wealth inequality, Gini index



Source: T-DYMM 3.0 – Authors' elaborations

Following the breakdown method proposed by Lerman and Yitzhaki (1985), it is possible to study the income (or wealth) inequality by its sources. This tool was already adopted in MEF *et al.* (2020), where in Section 6.1.1 we studied the breakdown of net wealth inequality using SHIW data. It is important to underline the fact that those results were computed without correcting the amount of financial wealth for the under-reporting (procedure explained in Appendix 2 of Chapter 1), therefore they are significantly different from the ones showed here. As illustrated in Figure 3.42, the Gini share of net wealth explained by financial wealth rises in the simulation years from about 45% to about 60% at the expenses of house wealth, whose relevance in explaining the overall wealth inequality decreases over time. This result, in line with the rest, is related to the increasing tendency of households in T-DYMM 3.0 to own financial wealth (83.7% of households hold a positive value of financial wealth in 2016, whilst 89.2% in 2070); indeed, if we further break down by the four financial activities we realize that the most relevant surge in the contribution to inequality is due to liquidity (a finding that is coherent with what was said at the beginning of the section regarding the spread of financial wealth due to the savings effect). One of the next steps in the results of the simulation will be to disentangle the role of different accumulation channels in shaping the final wealth results. In order to do so, we will use the same breakdown to compute the contributions to variation (i.e. the first difference) in the Gini of wealth exerted by the factors at work in the model: intergenerational transfers, savings, capital gains and end-of-service payments.

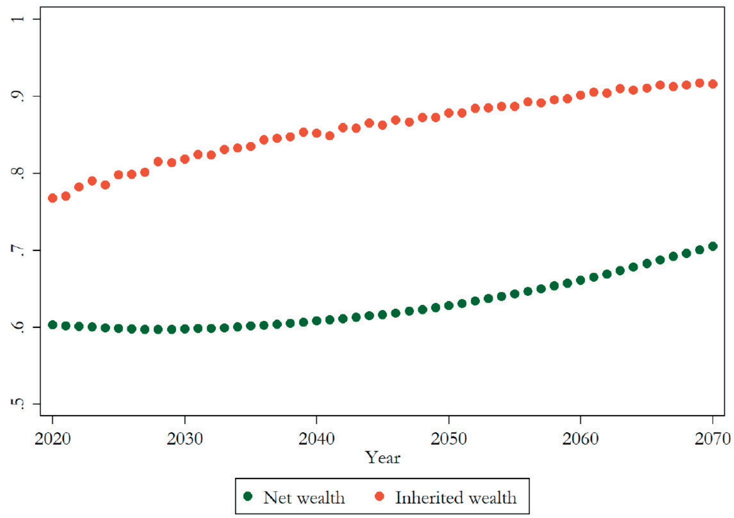
Figure 3.42 Net wealth inequality breakdown



Source: T-DYMM 3.0 – Authors' elaborations

Another key role in explaining the rise in wealth inequality is the one played by intergenerational transfers. The weight of this channel of wealth transmission and persistence has been strongly increasing in the most recent years in Italy: as showed by Acciari and Morelli (2020), the ratio between the value of total inheritance and donations and household income rose from about 10% in 1995 to about 18% in 2016. In our model, the role of transfers is significant as well. The level of inequality of total transfers (including *mortis causa* and *inter vivos*) is remarkably higher than net wealth inequality (with a Gini index beyond 0.8 for the entire simulation period, see Figure 3.43). Moreover, as shown in Figure 3.44, the increasing portion of wealth detained by elderly individuals (over 65 years of age) generates a higher probability of very strong effects of intergenerational transfers on overall inequality. Given the relevance of these processes, further research and policy scenarios will focus on the inclusion in the model of the inheritance tax.

Figure 3.43 Gini Index, net wealth and inherited wealth



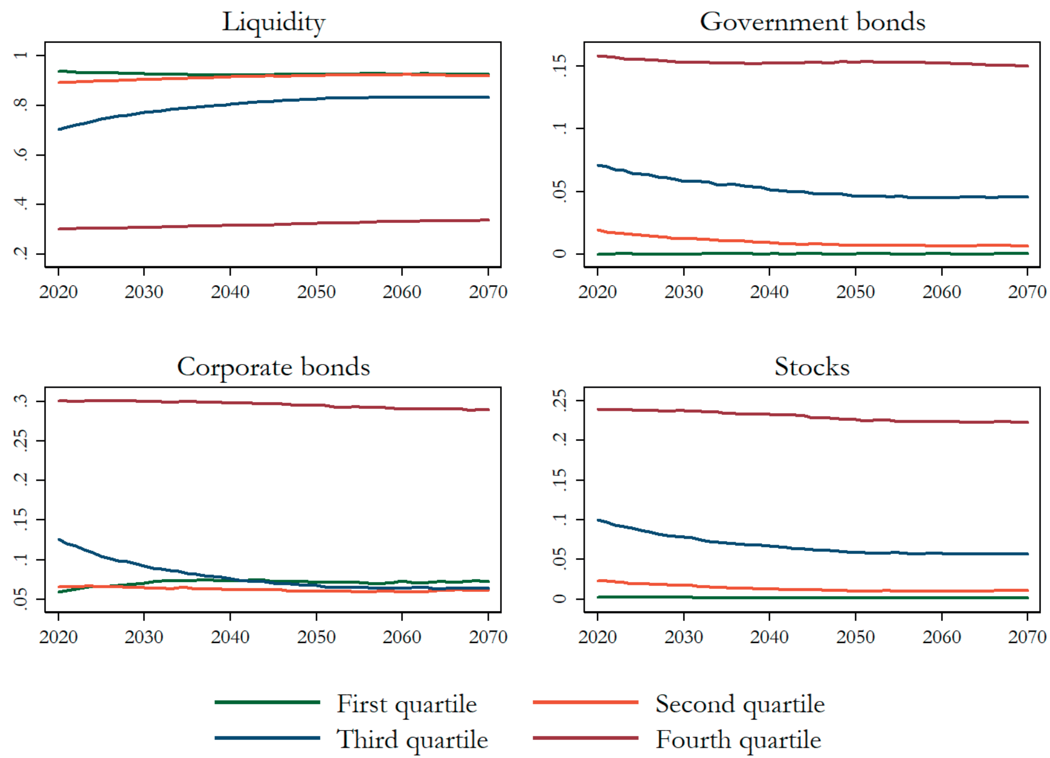
Source: T-DYMM 3.0 – Authors' elaborations

Figure 3.44 Net wealth by age

Source: T-DYMM 3.0 – Authors' elaborations

Finally, we show some results in terms of financial portfolio composition. As explained in Section 2.4, there are four types of financial activities in T-DYMM: liquidity, government bonds, corporate bonds and stocks. In Figure 3.45, we show the evolution in the ownership of such activities by financial wealth quartile: the richer quartile (fourth), as expected, owns a higher amount of stocks and a lower amount of liquidity throughout the period of simulation (this is mainly driven by the dynamic behavioural equations estimated on the panel component of the SHIW data and discussed in Section 2.4), the opposite holds for the less wealthy (those in the first quartile of financial wealth). The middle quartiles show more movement in their financial investments, however the overall picture is steady. The next steps will foresee the inclusion of some behavioural elements in the financial investment decisions that, interacting with the possible different scenarios regarding returns, may help to better understand the future of financial wealth also in the presence of any form of shock on the markets.

Figure 3.45 The evolution of financial activities by financial wealth quartile



Source: T-DYMM 3.0 – Authors' elaborations

3.5 Tax-Benefit Module

In this section, we will present the main results obtained for the Tax-Benefit module. The focus is on the redistributive effect of total transfers and taxes separately, as well as on the incidence and intensity of poverty. All the figures consider the individual as the unit of analysis, while income values are equivalised by using the OECD-modified equivalence scale. We discuss the results based on three income aggregates defined as follows:

Gross income before benefits (*Y*): includes labour income net of social security contributions and productivity bonuses granted to employees; rental income from residential properties; capital income; cadastral value of the main residence; retirement income (inability, old-age/seniority and survivors' pensions); and second- and third-pillar private pensions.

Gross income after benefits (*Y+B*): adds to the previous income definition the full list of in-cash benefits reported in Table 2.14.

Disposable income (*Y+B-T*): subtracts the personal income tax and proportional taxes listed in Table 2.13 from gross income after benefits.

The reader should keep in mind that zero values are always included in the calculations of inequality and poverty indices regardless of the income definition adopted[18]. Furthermore, we assume that tax-benefit monetary parameters (e.g. PIT brackets, threshold levels of tax expenditures, benefit amounts, and so on) follow nominal GDP growth starting from 2024, the first year after the forecast horizon of the latest Stability Programme for Italy at the time of writing.

3.5.1 Inequality levels and the redistributive effect of transfers and taxes

Figure 3.46 displays trends in income inequality for the overall population and for specific age groups. Given the profound changes in the elderly population due to the rapid increase in retirement ages and in employment rates for older workers, in what follows we shall address this category by analysing the position of those with ages equal to the Standard Pensionable Age [hereinafter SPA] and over[19]. We believe that, especially in the long run, a dynamic definition of the elderly better fits our purposes. Inequality in gross income before benefits does not vary significantly up to 2050 except for the elderly population, for whom inequality first increases up to

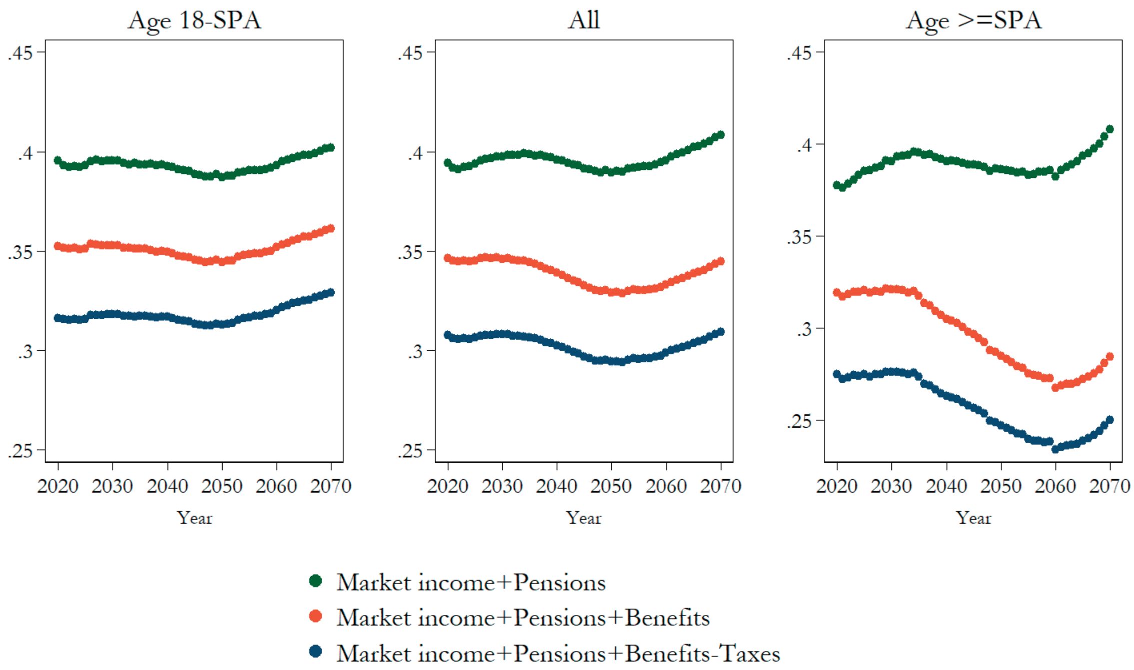
[18] The percentage of individuals with zero equivalised disposable income is rather stable and amounts to roughly 1% throughout the simulation period.

[19] We derive this terminology from the latest Pension Adequacy Report from the European Commission (2018). SPA coincides with the age requirement for our "Old Age 2" criterion.

2035 and then follows a downward trend[20]. From 2050 onwards, we observe a steep increase regardless of the reference population. This is due mainly to the increasing share and concentration of capital income[21]. Figure 3.47 plots the inequality trend of gross income before benefits first including and then excluding capital income. The non-inclusion leads to a flattening out of the curve with regard to the overall population, while inequality continues to decline when focusing on the elderly. As pension benefits granted according to NDC rules increase significantly their incidence on total pensions, inequality in gross income is bound to decrease.
Inequality in gross income after benefits and disposable income follows a similar trend to that observed for gross income before benefits. Simulated transfers contribute to a greater extent to the reduction of inequality than taxes in absolute terms[22]. This is true above all for the elderly population, where the combined effect of aging and lower pension benefits yields to a redistributive effect of transfers three times higher than that of taxes by the end of the simulation. In addition to this, still referring to the elderly population, the effect of the overall tax-benefit system results in consistently lower levels of inequality in disposable income.

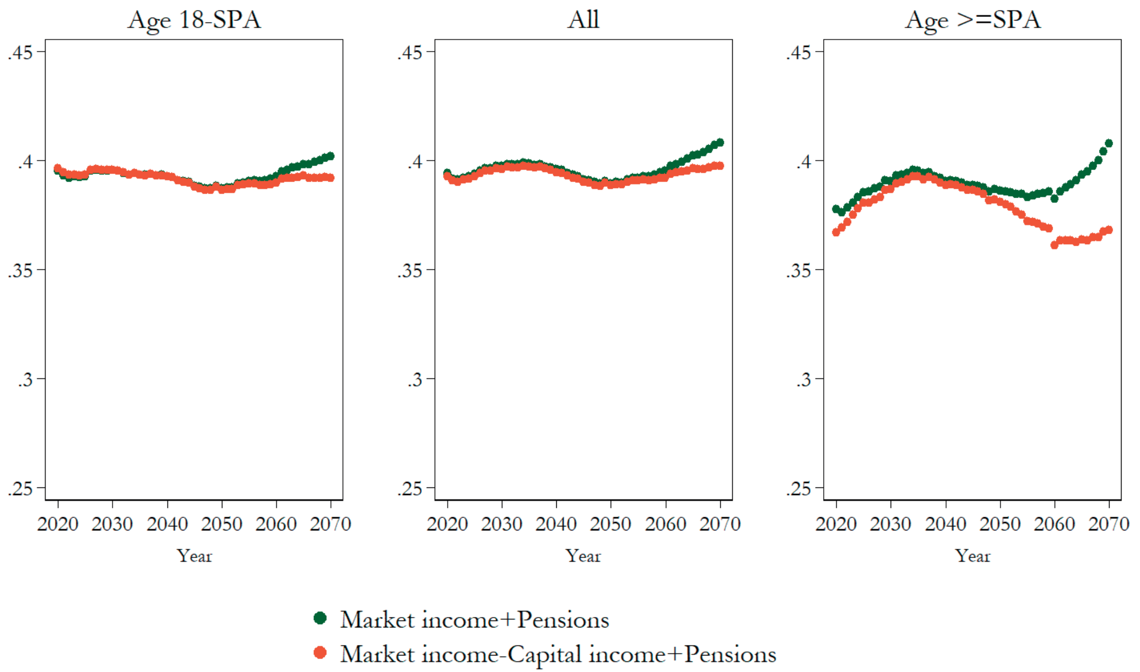
20 Visible small breaks in the series are due to the periodic update of SPA to changes in life expectancy. Because T-DYMM is an annual model, these updates produce a one-year shift about every 10 years.
21 Capital income accounted for 4.8% of gross income before benefits in 2020 and steadily increases to 9.8% in 2070. The concentration index of capital income with respect to gross income before benefits goes from 0.514 in 2020 to 0.645 by the end of the simulation. These figures may slightly differ from figures in Section 3.4 since here we refer to equivalised income values.
22 For the overall population, the redistributive effect of transfers was equal to 0.047 (0.058) in 2020 (2070), while taxes reduced inequality in gross income after benefits by 0.038 (0.034) in 2020 (2070).

Figure 3.46 Gini index for different income definitions



Source: T-DYMM 3.0 – Authors' elaborations

Figure 3.47 Gini index of market income plus pensions including and excluding capital income



Source: T-DYMM 3.0 – Authors' elaborations

We now move to the breakdown of the redistributive effect of transfers and taxes separately, for a better understanding of what drives inequality reduction from gross to disposable income. Following Kakwani (1980), the redistributive effect of taxes (i.e. the decrease or increase in inequality levels as measured by the difference between the Gini index before and after state intervention) can be broken down into three components:

$$[1] \quad RE = G_{Y+B} - G_{Y+B-T} = \frac{t}{1-t} K_T - R_T = \frac{t}{1-t} (C_T - G_{Y+B}) - R_T$$

where *t* stands for the average rate of taxes and *t*/(*1-t*) is the "average tax rate effect"; K_T is the Kakwani index measuring the "progressivity effect" of taxes and is given by the difference between the concentration index of taxes (C_T) and the Gini index of gross income after benefits (G_{Y+B}); K_T ranges between -1 (maximum regressivity) and 1 (maximum progressivity); finally, R_T is a residual that captures the re-ranking of individuals when taxes imply a different post-tax income order. R_T contributes only marginally to the redistributive effect leaving to average tax rate and progressivity effects what affects inequality levels the most.
This framework can also be extended to the measurement of the redistributive effect of transfers as follows:

$$[2] \quad RE = G_Y - G_{Y+B} = \frac{-s}{1+s} K_S - R_S = \frac{-s}{1-s} (C_S - G_Y) - R_S$$

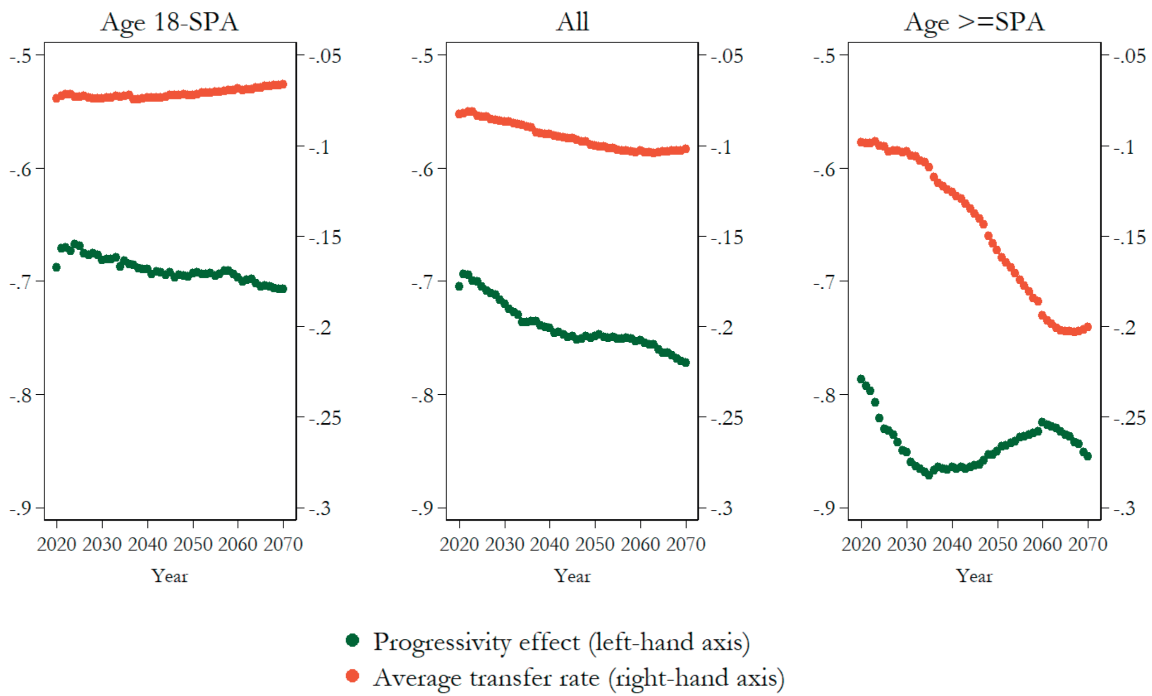
in this case, *s* represents the average rate of transfers and -*s*/(1-*s*) is the "average transfer rate effect"; K_S is the "progressivity effect" of transfers ranging between -1 (maximum progressivity) and 1 (maximum regressivity); C_S and G_y are equal to the concentration index of transfers and the Gini index of market income including pensions, respectively; finally, R_S stands for the re-ranking effect as a result of reordering in post-transfer income levels. The lower *s* (*t*), the higher (lower) is the value of transfers received (taxes paid) on average. Similarly, the lower the progressivity effect of transfers (taxes), the higher the proportion of total transfers received (taxes paid) by the poorer.
At the level of the overall population, individuals receive on average a higher share of transfers on gross income before benefits. Indeed, *s* varies from 0.083 to 0.102 by the end of the simulation as shown in Figure 3.48. Most of this increase is explained by the upsurge of *s* among the elderly population, while the working population sees a slight reduction over the years. Alongside this, what seems most interesting is the

dynamics of the progressivity effect. A higher share of transfers goes to poorer groups as K_S displays a steady downward trend for the overall population. This is true also for the elderly population during the period 2020-2035 where the equalising effect of the NDC scheme has not yet fully manifested itself. Afterwards, the progressivity of transfers bounces back as differences in income levels tend to be smaller, especially in retirement income. From 2060 onwards, we observe a change of direction that may be due to the increasing share of capital income components on gross income and thus leading to a rise in the number of individuals/households not meeting means-tested criteria.

As far as taxes are concerned, we register a gradual decrease in the average tax rate for the overall population up to 2060 (see Figure 3.49) which explains the reduction in the redistributive effect of taxes, followed by a slight recovery in the interval 2060-2070 as the share of capital income on gross income increases and so do proportional taxes on total revenue. The breakdown by age groups shows that the incidence of simulated taxes decreases remarkably for the elderly population only while working-age individuals pay on average about 17-18% of gross income after benefits. Tax progressivity is rather stable throughout the simulation period considering the overall population, but age-group analysis reveals a downward trend for the younger group that is offset by a steep increase among the elderly. As a result, a higher share of PIT on total taxes is borne by the working population with respect to the elderly by the end of the simulation[23]. This contributes to making PIT even more selective on specific categories. Recent changes in the tax treatment of several income components (more on this in Section 2.5.1) have already contributed to shifting the PIT burden from the self-employed and rental income recipients to employees and retirees, and the results of the simulation suggest that the PIT burden will be further concentrated on employees only as a result of lower pension benefits.

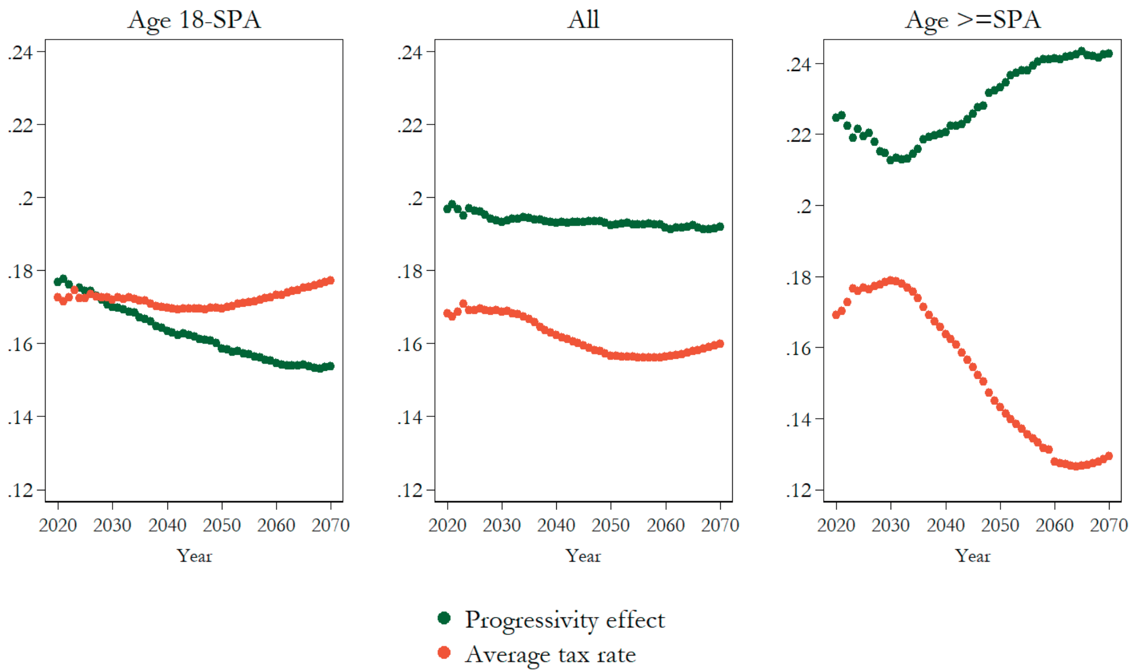
[23] At the level of the whole population, 9 (8) euros out of 10 of simulated revenue in 2020 (2070) come from PIT. The share of PIT paid by the working population amounted to 72.6% in 2020, for then increasing to 83.6% in 2070.

Figure 3.48 Progressivity effect and average transfer rate: from market income plus pensions to gross income after benefits



Source: T-DYMM 3.0 – Authors' elaborations

Figure 3.49 Progressivity effect and average tax rate: from gross income after benefits to disposable income



Source: T-DYMM 3.0 – Authors' elaborations

3.5.2 Incidence and intensity of poverty

Figures 3.50 and 3.51 illustrate the evolution of the incidence and intensity of poverty for the overall population and for subgroups by gender and age. The "headcount ratio" (*H*) is an indicator of the incidence of poverty and measures the share of the reference population with equivalised disposable income lower than the poverty threshold, which is 60% of the median equivalised disposable income calculated on the overall population. The "income gap ratio" (*I*) is an indicator of the intensity of poverty and is equal to the average income shortfall of the poor reference population from the poverty threshold:

$$[3] \qquad I = \frac{1}{q}\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right) = \frac{1}{q}\sum_{i=1}^{q}\frac{g_i}{z}$$

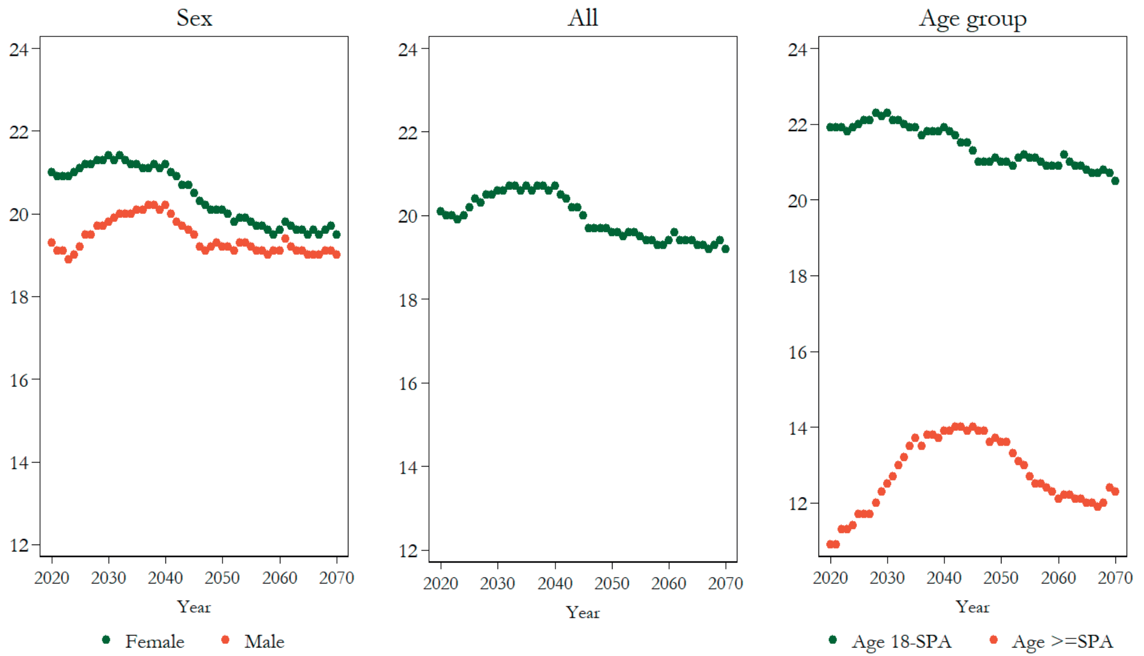
where z is the poverty threshold; y_i is the disposable income of the *i-th* poor individual; q refers to the total poor reference population; and g_i is the individual poverty gap. One can obtain the index known as "poverty gap", which relates the intensity of poverty to the overall population, by simply multiplying *H* by *I*[24].

For the overall population, we observe that the incidence of poverty first increases to around 21% up to 2040 and then decreases to 19%. On the contrary, the intensity of poverty shows a steady upward trend starting from 2045, meaning that individuals in poverty conditions undergo an average shortfall in disposable income of around 3.5 p.p. – expressed as distance from the poverty threshold – by 2070. Females have a persistently higher risk of being poor with respect to males which gets smaller over time, but we do not observe substantial differences in the intensity of poverty which increases in both cases according to the trend for the overall population. We also observe that working-age individuals are more likely to be poor (in relative terms) than the elderly, and that the gap in incidence levels between age groups narrows down as simulation time goes by. In addition to this, severity of poverty conditions increases for both age groups but working-age individuals are found to be consistently poorer. The social allowance and disability allowances, whose incidence amongst the elderly grows throughout the simulation period[25], play a major role in containing the intensity of poverty among the elderly.

[24] Alternatively: $PG = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{z-y_i}{z}\right)$, with n referring to the total population and z-y_i = 0 if $y_i > z$.

[25] The number of recipients of the social allowance and disability allowances (both means- and non-means-tested measures) amounts respectively to 7.8% (24.2%) and 14.6% (20.3%) of the elderly population in 2020 (2070). A large portion of the increase in the social allowance (*assegno sociale*) paid out is due to the fact that NDC pensioners are not entitled to the *integrazione al minimo* (see Section 3.3). While aligned probabilities to receive disability allowances slightly decrease over time by age class (see Chapter 2), the quota of individuals aged over 80 (more prone to disability) within the elderly group increases, thus driving up the percentage of recipients.

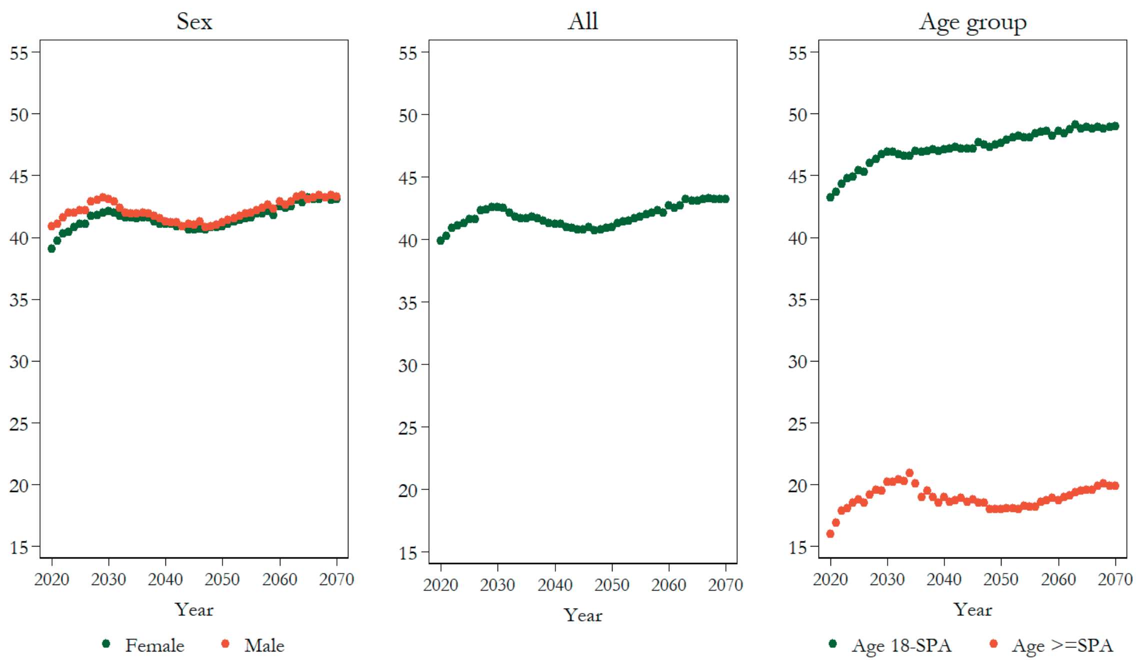
Figure 3.50 Headcount ratio (%) of disposable income by sex and age group



Note: T-DYMM's results may differ from Eurostat statistics for a series of reasons: i) Eurostat figures concern individuals over 64, while we compute figures for individuals with age equal to SPA and over; ii) Eurostat estimates are based on survey data, while for T-DYMM we use income values derived from administrative data; iii) by assuming the full take-up rate of transfers, we are bound to underestimate the incidence of poverty

Source: T-DYMM 3.0 – Authors' elaborations

Figure 3.51 Income gap ratio (%) of disposable income by sex and age group



Source: T-DYMM 3.0 – Authors' elaborations

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