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Pink queue and Double Standard: what Markov Chains uncover in academic career progressions

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Abstract

This study is the first modeling academic career progression using multi-state models, an approach that allows to compute additional quantities of interest never produced in this context, such as the probability of attaining specific academic positions over given time horizons and the average time required to reach them. Potential gender differences along these dimensions are assessed by comparing these metrics computed for male and female scholars separately, while accounting for productivity, individual preferences, and even seniority, which are often cited as explanations for women's disadvantage in academic careers. Leveraging a suitably-built highly informative dataset covering the universe of professors having worked in Italian universities between 2016 and 2021, we show a gap in the probabilities of career advancement that reduces with the career horizon but never vanishes, stabilizing around 2 (3) percentage points for those starting their career as Assistant (Associate) professors. In addition, we find that female scholars require up to two additional years to reach the highest academic rank (full professorship) compared with otherwise equivalent male counterparts, a phenomenon we label the "pink queue". Finally, we find a systematic misalignment in career advancement probabilities between male and female scholars with comparable productivity, whereby women achieve the same advancement chances as men only when they attain higher productivity levels, suggesting the presence of a potential "double standard".

JEL Codes: J16, J71

Keywords: gender gap, Markov chain, university, productivity, pink queue, double standard

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1 Introduction

The labor market exhibits substantial gender disparities (see for example the IMF Gender Note 2024 Gomes and Rijal (2024)). Academia, although a highly specific and relatively narrow segment of the labor market, largely reflects these disparities. While women's participation in academia has increased considerably (see Iaria et al. (2022) and references therein), gender imbalances at the highest academic ranks such as full professors, department heads, and rectors remain marked and represent a clear example of the glass ceiling. In Italian universities, for instance, only about 26 percent of full professors are women, despite equal or higher shares of female graduates and PhD holders in several fields Sagramora et al. (2023). The observed gap amounts to roughly 4 percentage points in promotion to Associate Professor and nearly twice that for advancement to Full Professor, even after controlling for productivity and habilitation Brunetti et al. (2023).

Academia provides a particularly suitable setting for the study of gender gaps due to its institutional and structural characteristics. Specifically, it is an environment in which individuals are highly educated and display less heterogeneity in background and career trajectories than those in the general labor market. As a result, gender gaps measured in this context are likely to be less affected by confounding factors arising from unobserved population heterogeneity, which are typically difficult to control. For this reason, estimates derived from this setting, despite the peculiarity of the context, can yield insights of broader general interest.

Typically, gender gaps in access to and career advancement in academia have so far been investigated using classical econometric models, in which the outcome of interest is regressed on the gender of the scholar and a set of other regressors (e.g., Ginther and Kahn (2009), Ginther and Kahn (2004), Baker (2012), Filandri and Pasqua (2021), Brunetti et al. (2023)). While this approach has produced valuable evidence, it is essentially static and does not allow direct evaluation of dynamic career quantities such as the time required to reach a given rank or the probability over different horizon.

In contrast, gender (and other) gaps in other sectors of the labor market have been analyzed with a variety of methodologies, including multi-state models. These models incorporate the time dimension and thus allow researchers to estimate not only the probability of reaching a certain working position but also the timing of such transitions and the duration spent in each state (the working life expectancy as in Dudel and Myrskylä (2017), Dudel (2021), Lorenti et al. (2019), Lorenti et al. (2024), Lozano and Renteria (2019)). This methodological flexibility is particularly appealing in contexts where career progression unfolds over long horizons and where timing itself may be an important dimension of inequality.

This paper lies at the intersection of these two strands of literature. We provide new evidence and measurement of gender gaps in academia by modeling, for the very first time, academic career progression through a Markov multi-state model. This approach enables a dynamic assessment of gender differences in both probabilities and expected times of transition across academic ranks, thereby enriching and complementing existing empirical analyses of gender disparities in academic careers. To this end, we rely on a rich dataset covering the universe of professors who worked in Italian universities between 2016 and 2021, purpose-built by merging three data sources: administrative data from the Italian Ministry of Universities and Research (MUR), which provide information on all individuals holding permanent academic positions; data from the National Agency for the Evaluation of Universities and Research, which supply information on scientific habilitation; and bibliometric data from Elsevier's Scopus, which are used to measure scientific productivity.

Italian academia offers an ideal setting for measuring this gap because its institutional features mitigate several of the most common explanations used to justify gender disparities. A frequent argument is that women avoid promotions and positions of responsibility to prevent increases in workload that may conflict with family or personal duties (Croson and Gneezy (2009)); another is that women tend to shy away from competitive environments (Niederle and Vesterlund (2007)).

In the Italian academic system, the first argument is weakened by the fact that career advancement is associated with higher remuneration but does not necessarily entail a heavier workload, unlike many positions in the private sector. Teaching hours are fixed by law and are identical for associate and full professors, while additional administrative responsibilities are optional rather than mandatory. As a result, workloads remain largely stable across ranks, leaving little scope for work–life balance concerns to explain lower female participation in promotion processes.

The second argument is addressed by the structure of the promotion system in Italian universities. Promotion follows a two-step process: scholars aspiring to become associate or full professors must first obtain the National Scientific Habilitation (NSH) and, only after obtaining it, can apply to local competitions announced by departments. Since obtaining the NSH requires an active application, scholars who hold this qualification have explicitly signaled their willingness to compete for promotion. We exploit this institutional feature to mitigate the concern that women systematically avoid competitive environments.

We compute the gap by comparing the probabilities over different time horizons and the average time of career progression for men and women. We also control for scientific productivity, another argument put forward in the literature as a potential driver of the observed gender gap. We do so by grouping scholars on the basis of their individual h index, which is a combined indicator of scientific productivity and scientific impact.

We focus in particular on measuring the probabilities and the average time of transition from the entry-level positions, namely Tenured Researcher (TR) or Tenure-track Associate Professor (TAP), to Full Professor (FP), and from Associate Professor (AP) to Full Professor.

On the one hand, our results confirm the evidence reported in the relevant literature, documenting the existence of a gap between male and female scholars in terms of the probability of reaching higher career steps. On the other hand, our results reveal further interesting patterns. Specifically, since we are able to evaluate this gap over different time horizons, we can report that women appear more disadvantaged in the short term, while the gender difference tends to diminish over longer horizons. In particular, the gender gap in the probability of reaching the state of full professor over a 10-year horizon is about 9 percentage points for those who are currently TR and/or

TAP, and about 4 percentage points for those who are currently AP. If, instead, a 40-year horizon, which ideally covers the entire career span of scholars, is considered, these figures decrease to about 3 percentage points for TR and TAP, and to about 2 percentage points for AP, respectively. These long-term figures, which are remarkably in line with those reported in studies dealing with similar contexts (see, e.g., Filandri and Pasqua (2021), Brunetti et al. (2023)), show that the gap between male and female scholars in terms of the probability of reaching the highest academic rank, although it narrows over longer career horizons, never vanishes.

This result is also confirmed when we examine the gap in terms of time. Female scholars reach promotion to higher ranks one to two years later than otherwise-similar male scholars. These patterns support the idea that men are promoted first, while women have to wait longer for their turn, a phenomenon we label as the *pink queue*.

We also report evidence of an academic system that does reward merit: the higher the level and the impact of the scientific productivity of the scholar, as measured by his/her h index, the higher the probability of being promoted to higher ranks and the shorter the waiting time. However, although this merit-reward relationship holds for both men and women, we observe a systematic misalignment between the metrics of male and female scholars of comparable scientific productivity. In particular, we report that female scholars belonging to a certain quartile of scientific productivity display promotion probabilities and time to visit which are in line with those of male scholars with a quartile-lower scientific productivity. This evidence suggests that women must demonstrate superior performance compared to men to get the same chances and the same timing to be promoted. This finding recalls the so-called *double standard*, where selection criteria are not applied uniformly across different categories of candidates.

Our results have been shown to be remarkably robust. Indeed, they remain qualitatively unchanged when, exploiting the information about the year of first publication, we derive the demographic cohort and the academic age of the scholar and repeat our analysis controlling for them. Similarly, the evidence remains the same when we restrict our analysis to scholars belonging to bibliometric sectors only.

Thus, our study, that applies multi-state methods to the context of Italian academic promotions, not only represents a novelty in terms of the approach used to assess the gender gap in promotion probabilities, but also provides a picture of the phenomenon over different time horizons and, more originally, an assessment of the gender gaps along other dimensions, such as time to promotion, while simultaneously taking into account productivity and seniority.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature, Section 3 describes the Italian setting, and Section 4 illustrates the data and the methodology used. The main results are presented in Section 5 and their robustness is discussed in Section 6. Finally, Section 7 concludes.

2 Literature

This paper lies at the intersection of two streams of literature.

The first one deals with gender gaps in the academia, which, according to Iaria et al.

(2022) are still relevant. In their work, Iaria et al. (2022) analyze gender disparities in academia using the largest database of university academics ever compiled, combining historical and modern data with publication and citation records. Despite universities experienced a significant increase in the percentage of women hired from 1900 to 2000, women remain persistently underrepresented, especially in STEM fields and in more renowned institutions, and continue to face struggles for equal opportunity and recognition, as further documented in different scientific disciplines and countries by many other studies (Ginther and Kahn (2004), Ginther and Kahn (2009), Baker (2012), Ooms et al. (2018), Howe-Walsh and Turnbull (2016), Seierstad and Healy (2012), Sara Diogo and Breda (2021)). This study contributes to this literature by leveraging an approach, namely Markov multi-state models, that not only is completely novel to this setting, but also enables a dynamic assessment of gender differences in transition probabilities and expected transition times across academic ranks, thereby providing additional insights to the existing empirical evidence on gender gaps in academic careers.

Many studies in the literature dealing with gender gaps in the academia have also sought to explain the potential causes of the observed gaps. One of the most widely recognized driver is women's lower productivity, in terms of both number of publications and number of citations (Larivière et al. (2013); Mairesse and Pezzoni (2015); Nielsen (2016)). On the one hand, this lower productivity may be related to family duties and childbearing responsibilities (Cole and Zuckerman (1984); Stack (2004); Ceci and Williams (2011); Lutter and Schröder (2020)), which, in turn, may also explain why women tend to have weaker international networks (Beaudry and Larivière (2016)). On the other hand, there is also evidence that women face higher barriers in the publishing process (Card et al. (2020)), experience longer peer-review times (Hengel (2022)), and that their publishing success is influenced by the gender composition of editorial boards (Bransch and Kvasnicka (2022)).

Another commonly discussed explanation for the gender gap in academia draws on evidence suggesting that women exhibit greater risk aversion and lower self-confidence (Barber and Odean (2001)) and tend to "shy away" from competition (Niederle and Vesterlund (2007); Azmat and Petrongolo (2014); Bosquet et al. (2019b); Adamecz-Völgyi and Shure (2022); Paola et al. (2015); De Paola et al. (2017)).[1] Nevertheless, despite these attempts to explain the phenomenon, the gender gap in academia remains largely unexplained. Focusing on Italy, Filandri and Pasqua (2021) and Brunetti et al. (2023) show that, even after controlling for productivity and self-confidence, a gap of approximately 3 percentage points persists in promotion rates from assistant to associate professor, and of about 7 percentage points from associate to full professor.

To conclude, the literature on gender disparities in academia consistently highlights two main factors that, although they do not fully account for these disparities, substantially contribute to them: lower scientific productivity and a reduced inclination to participate in competitive environments. In our analysis, we explicitly control for both factors, which enables us to evaluate gender differences in academic career advance-

[1] Other factors have then been proposed: for instance, Brunetti et al. (2023) prove that promotions within the same institution tend to penalize women more, suggesting that women are typically disadvantaged when it comes to negotiation skills and bargaining. Last, Brunetti et al. (2024) found a strong association between career advancement of female scholars and the share of women the pool of professors who decide on promotions, pointing toward a role for female representation in the decision boards.

ment net of these two widely acknowledged driving forces.

The second stream of literature we touch upon is the one using multi-state models, which have been largely used to explore gender and other gaps in many sectors of the labor market, but never to academia.

For example, Dudel and Myrskylä (2017) investigate working life expectancy at age 50 in the USA, using data from the Health and Retirement Study covering the period 1992-2011. The analysis highlights persistent gender, racial, ethnic and educational inequalities in employment, reflecting the complex interaction of labor market attachment, mortality, and policy regimes. More recently, using the same methodology and again HRS data spanning the period 1998-2016, Sharma et al. (2023) investigate the co-occurrence of cognitive impairment and limitations in activities of daily living (co-impairment) among U.S. adults aged 50+. The study reveals significant disparities by gender, race, ethnicity, nativity, and education.

Lozano and Renteria (2019) use multi-state table models to assess gender differences in the Spanish labor market life expectancy over the period spanning 1986 to 2016, highlighting a significant reduction in the gender gap in employment, especially after the 2008 recession. Similarly, Lorenti et al. (2019) model transitions between labor force states (employed, unemployed, inactive, retired) using a Markov chain approach, thus being able to measure the expected years spent in employment over a lifetime, and analyzing trends by gender, occupation, and region. Using Italian longitudinal social security data covering the 2003-2013 decade, they find that during the Great Recession, the working life expectancy dropped for both genders, but more for women, and that regional disparities widened. Again, Lorenti et al. (2024) use multi-state models and compare employment trajectories from ages 40-74 in Finland, Italy, and the USA, providing a comprehensive analysis of gendered parenthood-employment gaps across different welfare systems. They find that in Finland, employment gaps by gender are small, while in Italy, traditional gender roles and limited policy support exacerbate employment penalties for mothers. The USA falls somewhere in the middle, reflecting a less generous policy context and persistent penalties for women with multiple children.

Finally, Dudel (2021) has further contributed to this literature by providing new methods for discrete Markov chains, that allow to derive complete distributions, rather than simple averages, for times to first entry to and to final exit from subsets of states, thus allowing a more comprehensive analysis of event timing and state occupancy. Applying this modified methodology to social security data on Spanish male workers covering the 2004–2013 period, he finds increased inequalities in working life duration.

This study leverages Dudel (2021)'s enriched methodology to assess existing gaps in academic career progression in the probability of attaining and average time required to reach top academic positions.

3 Institutional Background

The Italian case is of interest and well suited to our analysis for several reasons, which we outline in what follows.

The Italian academic system comprises several temporary junior positions, whose titles have changed over time through different reforms, but which are essentially post-doctoral or fixed-term research roles without a tenure track or any promise of future absorption into the system. Beyond these positions, there are, with some variations across reforms, three main ranks (usually referred to in Italian as "fasce"). The lowest rank is an entry-level position with a tenure track. In the pre-reform system, this corresponded to the Assistant Professor role ("Ricercatore a tempo indeterminato"), which we refer to here as Tenured Researcher. The Gelmini Reform (Law 240) later abolished this figure and introduced two new positions: a non-tenured assistant professor ("Ricercatore di tipo A"), and a Tenure-track Assistant Professor ("Ricercatore di tipo B"), which we refer to here as Tenure-track Associate Professor (TAP). The TAP position carries a three-year contract that leads to an (almost) automatic promotion to Associate Professor, provided the scholar obtains the National Scientific Habilitation (NSH) in the relevant scientific sector within the contract period [2]. The second rank of the system consists of Associate Professors, and at the top are Full Professors. Once employed in a permanent position in the Italian academic system, individuals typically remain in the system until retirement or death, for this reason it is not of particular interest to study the length of working life while it is more relevant to focus on probabilities and time to upgrades in the career path.

Career advancement follows a two-step procedure. First, scholars must obtain the NSH, granted by a national committee of full professors in the relevant subfield. Second, scholars holding the NSH may apply to competitions conducted locally at the department level.[3]

Some considerations are in order. First, professors' salaries at Italian universities are non negotiable and gender neutral, as they are set by the Ministry of University and published in standardized salary tables. Salaries can increase significantly only through career advancement.[4] This implies that, in the Italian academic context, gaps in career advancement can be seen as gender pay gaps (for further details on the Italian context (see, e.g., Filandri and Pasqua (2021), and Brunetti et al. (2023, 2024)).

Second, academic career upgrades come with an increase in remuneration but not necessarily with longer working hours, unlike many private-sector jobs. In fact, associate and full professors have similar obligations. Teaching loads (set by law) are identical, and additional administrative tasks are not mandatory. Moreover, with very few exceptions (such as Head of Department, Dean, or Rector), administrative responsibilities can be assigned to either associate or full professors without distinction. In other words, promotions result in higher salaries but do not necessarily imply an increase in working hours, effort, or job responsibilities. Thus, since associate and full professors share the same workload, there is no clear reason why women should refrain from competing for promotion. Hence, the Italian case allows us to address a common

[2] In 2022, a new legal reform introduced further changes to these entry positions, although this occurred after the period covered by our analysis.

[3] Departments announce public calls specifying the rank (associate or full professor), the scientific sector, and, in some cases, a brief description of the desired candidate profile. A local committee of professors then evaluates the applicants' CVs and selects the winner.

[4] Salaries also undergo minor and largely automatic increments based on seniority within the same career level.

argument suggesting that women are not promoted because they do not apply for promotion in the first place fearing an increase in the workload they could not bear. This is in line with what Bosquet et al. (2019a) report working on the promotion system for French academic economists. Indeed, as they put it:" *female associate professors should not feel more constrained in terms of combining career and family duties by becoming full professors; hence, there is no obvious reason why they would prefer not to be promoted*" (p. 1021).

Last, the Italian system requires scholars aspiring for career advancement to *actively* apply for the NSH. [5]. Leveraging this specific aspect of the Italian academic system, in our application, we focus on the career trajectories of scholars having been granted - and hence having actively applied for - the NSH. In this way, we are reassured that the findings are not driven by the common argument that women tend to shy away from competition, which is often mentioned as a possible reason for gender differences.

4 Data and Methodology

4.1 Dataset

The data used for the empirical analysis are taken from three different sources: Italian Ministry of Universities and Research (MUR), the National Agency for the Evaluation of Universities and Research (ANVUR), Elsevier's Scopus.

The first one provides the universe of professors having worked in all Italian Universities between 2016 and 2021.[6] For each professor, the data report name and surname, gender, and academic position (as of December 31 of each year), which we categorize as follows: junior assistant professors, Tenured Researchers (TR), Tenure-track Associate Professors (TAP), Associate Professors (AP), and Full Professors (FP).[7] From this initial dataset we dropped all observations whose position is "Incaricato" or "Assistente di r.e." or junior assistant professors. This is done given our focus on the career advancement of University permanent staff, rather than on the recruitment of new scholars. We then eliminated all namesakes, that is, professors with the same name and surname (around 4.61% of the cases), as well as all observations with missing information about the scientific sector. This is done because the merge with the other two data sources, described in what follows, is done based on name and surname, and we want to avoid any risk of misidentification.

The second source of data, reporting the name and surname, as well as the scientific sector, provides all the scholars accredited with the National Scientific Habilitations

[5] Further details on the NSH and on local selection procedures can be found in Brunetti et al. (2024)

[6] Data retrieved from the MUR website, https://cercauniversita.cineca.it/php5/docenti/cerca.php

[7] The detailed list of possible positions includes: Ordinario, Straordinario, Straordinario a tempo determinato and Ordinario r.e. (which we gather in the state "Full professor", FP), Associato, Associato non confermato, and Associato confermato (gathered in the state "Associate Professor", AP), Ricercatore, Ricercatore non confermato (collapsed in the single state "Tenured Researcher", TP), Ricercatore a tempo determinato di tipo B (according to either 2010 Gelmini Law or 2005 Moratti Law, both full and part time, gathered in the category "Tenure-track Associate Professor. TAP) and Ricercatore a tempo determinato di tipo A (either full or part time), belonging to the category of "Junionr assitant professor". Residual positions are "Incaricato" and "Assistente di r.e.".

(NSH) up to 2021.[8] In merging these two datasets, three cases are possible: i) professors working in the Italian academia who got qualified; ii) professors working in the Italian academia who do not got qualified; and iii) individuals not currently working in Italian universities who got qualified. Since this study aims to assess the potential gender gap in academic career advancements, we focus only on professors from the first two cases and drop all observations belonging to the third case.

The third and last dataset was suitably generated for this analysis by downloading, for each professor in our dataset having a Scopus webpage (about 30,652 scholars), the year of his/her first publication, which we use to derive a proxy for age (or, academic age) as well as his/her *h* index, conventionally used as a proxy for the scientific productivity.[9]

From the merged dataset, we then dropped a few scholars for whom we observed career "anomalies" (e.g., demotions from Associate professors to Tenured Researchers, or from Full to Associate professors), those accredited more than 10 NSH, and all those entering the dataset as Full professors, since for these scholars no further career advancement is possible. Finally, we dropped a few scholars whose first publication is before 1980, to clean up our analysis from scholars close to retirement and/or careers longer than 45 years.

Our final dataset counts 30,130 unique professors who have worked for at least two years in the Italian academia during the period spanning between 2016 and 2021.

Table 1 reports summary statistics of the h index distribution on the final sample, by disciplinary area. We can observe that the *h* index is highly heterogeneous across disciplinary areas. The hard sciences are characterized by higher and more variable values, while the humanities and economics show lower values. In particular, Literature and Law are no-bibliometric disciplines in which the *h* index is not a reliable measure of productivity, as their scholarly output — often published in Italian and mainly consisting of books or essays — is not fully covered by databases such as Scopus or Web of Science.

In the light of this, each of these scholars has then been classified by productivity according to her/his relative position with respect to all other Italian scholars in her/his scientific sector. [10] More specifically, we derived the quartiles of the distribution of the *h* index for each of the 68 scientific sectors, in order to account for the huge variability across different disciplines. Letting $q_{1,j}$ be the first quartile of the distribution of the *h* index in scientific sector j, we gathered all scholars with *h* index lower than $q_{1,j}$

[8]Data are taken from https://abilitazione.miur.it/public/index.php. Note that for privacy reason the names of those not qualified are removed 120 days after the publication of the accredited Habilitations.

[9]Introduced by Hirsch (2005), the *h* index is a widely-accepted quantitative metric to jointly assess scholars' productivity and their impact. A scholar *h* index is equal to *h* if *h* of their papers have each received at least *h* citations, while the remaining papers have fewer than *h* citations.

[10]The scientific disciplines of the Italian university are divided into 14 disciplinary areas, articulated in 68 sectors, further divided into 184 sub-sectors. For example, within the macro-disciplinary Area 13- Economics and statistics, there are 4 sectors, namely Economics (13/A), Business and Management (13/B), Economic History (13/C), and Statistics and Mathematics for Economic Decisions (13/D), in turn articulated in 15 sub-sectors: 5 for Economics (Political Economy, Economic Policy, Public Economics, Applied Economics and Econometrics), 5 for Business and Management (Business Economics, Management, Organization studies, Financial Markets and Institutions, and Commodity sciences), 1 for Economic History, and 4 for Statistics and Mathematics for Economic Decisions (Statistics, Economic Statistics, Demography and Social Statistics, and Mathematical methods of economy, finance and actuarial sciences).

Table 1: Descriptive statistics of the h index, by scientific area

Area	Mean	Std.Dev	Median	Min	Max	N
Math	13.84	6.65	13	0	57	1722
Physics	40.75	29.61	30	0	142	1517
Chemistry	29.01	9.93	28	0	141	1802
Science	21.54	7.89	20	3	53	661
Biology	26.34	9.63	25	0	94	2897
Medicine	30.17	14.33	27	0	144	5243
Agric & Vet	19.99	8.78	19	0	73	1872
Architecture	10.62	9.80	9	0	68	1980
Engineering	21.35	8.60	20	0	92	3438
Literature	1.64	2.34	1	0	23	2093
History and pedagogy	7.73	9.16	3	0	71	2423
Law	1.51	4.23	1	0	105	959
Econ & Stat	8.41	5.96	7	0	74	2546
Social Sciences	3.56	3.65	2	0	27	978
Total	18.82	15.84	17	0	144	30130

The table reports the main descriptive statistics for the h index, by scientific macroareas.

in the group denoted by Q1. Those will thus represent the lowest 25% in terms of productivity of their scientific sector. Similarly, Q2 group gathers those scholars whose h index is above $q_{1,j}$ but below the sector-specific median, $q_{2,j}$, and Q3 group gathers those with h index above the median but below the sector-specific third quartile, $q_{3,j}$. Last, Q4 group includes all scholars whose h index is higher than $q_{3,j}$, that is the best 25% scholars, in terms of sector-specific scientific productivity.

Table 2 reports the size of the sample, dissected by gender, and productivity quartiles.

Table 2: Distribution of the final sample, by gender and quartile of h index

Sector-specific h index quartile	(1) M	(2) F	(3) Total	(4) %M	(5) %F
Q1	5236	4189	9425	29.1%	34.5%
Q2	4075	3101	7176	22.7%	25.5%
Q3	4065	2681	6746	22.6%	22.1%
Q4	4609	2174	6783	25.6%	17.9%
Total	17986	12145	30130	1	1

Columns (1), (2) and (3) of the table report the absolute number of male, female and total scholars in the final sample, respectively, by quartile of sector-specific h index. Columns (4) and (5) report the relative frequency of male and female scholars, respectively, again by quartile of sector-specific h index.

Males represent 59.3% of the total sample and are the category more represented across all quartiles of productivity. Moreover, the gap in representation widens with the productivity quartiles, with men definitely more represented in the upper quartiles (gap of 11.1% in the lowest quartile, as opposed to 35.9% in the top quartile).

4.2 Methodology

We model career advancements in a multi-state discrete-time Markov model (Hoem (1977) Skoog and Ciecka (2010)), where the states of the Markov chain represent the various steps of the academic career, and the transitions correspond to movements between these roles.

More specifically, thinking of the Italian academia, as already explained in Section **??**, four possible academic positions are possible, namely: Tenured Researcher (TR), Tenure-track Associate Professor (TAP), Associate Professor (AP) and Full Professor (FP). Besides, recalling that after the Gelmini reform each position potentially undergoing a promotion (TR, TAP, and AP) can either be qualified or not with the NHS, a total of 7 transient states are possible, namely: TR, TR_H, TAP, TAP_H, AP, AP_H, and FP. [11] The model also includes an absorbing state, labeled "Exit," which encompasses exit from the academic system due to retirement, death, a shift to a non-academic career, or relocation abroad.

Accordingly, the transitions represent scholars' transitions from one of these 8 states to another at each step of the chain. These could represent: (i) remaining in the same state (e.g., being a FP in a period and remaining FP the next period), (ii) moving from a non-habilitated state to a habilitated state while retaining their current academic position (e.g., from TR to TR_H), or career advancement from one (habilitated) state to a higher-level state (e.g., from TR_H to AP), or transition towards the absorbing state (e.g., from FP to $Exit$ in case of retirement). Recalling that professors cannot get back to previous positions, we assume a Markov chain where demotion is not allowed. The chain is graphically represented in Figure 1.

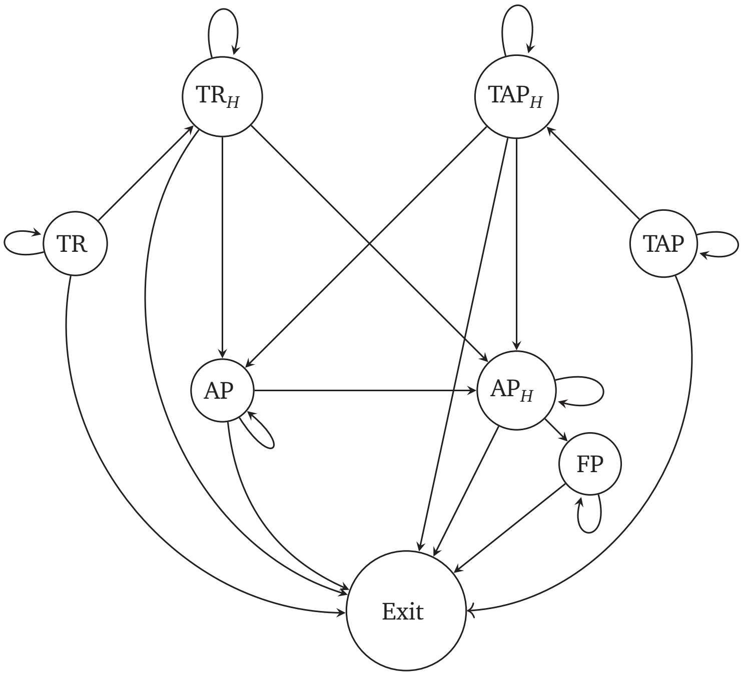
This study focuses on gender gaps in career advancement. Hence we will present results referred to transitions from NHS-qualified career levels only, and no evidence will be presented on, e.g., transitions from a non-qualified career state to the same NHS-qualified career state, or from any state to the absorbing Exit state. Moreover, all quantities will be estimated for male and female scholars separately, so that a comparison between the metrics obtained for the two groups will highlight potential gaps.

Specifically, we will focus on the transitions to the state of Full Professor (either in one or in multiple steps), which represents the highest working position in an academic career and - typically - the hardest to achieve for female scholars. More specifically, we will present results for the following transitions: (i) from NSH-qualified Tenured Researcher to Full Professor, i.e., from TR_H to FP; (ii) from NSH-qualified Tenure-track Associate Professor to Full professor, i.e., from TAP_H to FP, and (iii) from Associate Professor to Full Professor, i.e., from AP_H to FP.

Transitions (i) and (ii) are of particular interest since they cover the entire span of an academic career, the former under the previous legal framework, and the latter under the reformed recruitment system introduced with the Gelmini Reform. To compare (i) and (ii) thus amounts to compare different "generations" of scholars, who have entered the academia under two distinct recruitment systems. The transition (iii) on the other

[11] Recall that the related literature applying Markov models to the labor market often focuses on working life expectancy and distinguishes among states such as active, inactive, and retired (Lorenti et al. (2019)). In contrast, we focus specifically on tenured individuals within the Italian university system, where, due to institutional mechanisms, individuals rarely leave once they enter.

Figure 1: The Markov chain model.



The Markov chain model. The states correspond to various academic roles within the Italian academia, namely: Tenured Researcher (TR), Tenure-track Associate Professor (TAP), Associate Professor (AP), and Full Professor (FP). All of these roles but the FP, can either be qualified with the NSH (denoted with $_H$) or not. The "Exit" state is absorbing, representing departure from the academic system due to retirement, death, career change, or relocation abroad. Arrows indicate possible transitions between states and no possibility of demotion is allowed.

hand, is of particular interest as it typically represents the one where the gender gap is the highest in magnitude (see, e.g., Baker (2012), Bertrand et al. (2019), Iaria et al. (2022), Brunetti et al. (2023), among others). Moreover, a comparison between (i) and (ii) on the one hand and (iii) on the other will reveal potential differences in the probability and timing of reaching the highest-rank career level between such different career stages.

Once again, notice that we will present results concerning transitions from NSH-qualified states only. This is done not only because under the current legislation NSH is a necessary requirement for career advancements, but also because NSH requires an application. In other words, NHS-qualified scholars, who had to actively apply for it, can reasonably be considered scholars actively seeking promotion. Thus, restricting our attention to NHS-qualified scholars amounts to restricting the attention to scholars who have similar ambitions of career progression, and hence to - at least partially - control for the argument that women tend to shy away from competition, one of the most widely put forward when it comes to gender gaps in promotions (see, e.g., Niederle and Vesterlund (2007), and Brunetti et al. (2023) and references therein).

Using our rich data set, which also provides information about the h index of each scholar, we are also able to take scientific productivity into account, i.e., another argument typically considered as a potential driver of observed gender gaps (see, e.g., Larivière et al. (2013); Mairesse and Pezzoni (2015); Nielsen (2016)). In order to do so, we proceed as follows. First, we obtained the quartiles of the distribution of the h index for each of the 68 scientific sectors. This is done to clean out the huge degree of heterogeneity observed across the different sectors. Next, we classify each scholar according to the relative position of his/her h index compared to sector-specific quartiles, as already explained above. The metrics of interest in the Markov chain are thus derived separately for each group of scholars, belonging to the same quartile of the sector-specific h index. In this way, comparing these metrics allows to highlight potential differences between scholars based on their different levels of scientific productivity, and comparing these metrics dissected by gender, allows to unveil potential differences between male and female scholars with comparable scientific productivity. In other words, we can unveil potential gender gaps, controlling for the level of scientific productivity.

Modeling academic career progression using a Markov chain has the great advantage of deriving the distributions of several quantities of interest, including the probability of visiting a state (or a subset of states), the waiting time to first visit of and to final exit from a state, and hence the time spent in a specific state. In this study, we focus on the probability of visit and on the time to first visit of a certain state, i.e., of a certain career level, since our primary is studying career progression (rather than the duration of time spent in a given position). Moreover, in order to assess any potential gender differences in the career progression, we compare the quantities derived on the subset of male scholars with those derived on the subset of female ones.

In order to derive these quantities, we rely on the methodology implemented in Dudel (2021), which is briefly sketched in what follows.

Let $\{Z_t\}_{t\geq 0}$ denote a discrete-time Markov chain, where time is assumed discrete $t = 0, 1, 2, ..$, and where each variable Z_t takes values in a finite set of possible states $\mathscr{S} = \{s_1, s_2, \ldots, s_m\}$. In our application $\{Z_t\}_{t\geq 0}$ represents the evolution of a scholar career through different stages over time. Moreover, in our setting $m = 8$, corresponding to the 7 possible transient states plus the absorbent one, as pictured in Figure 1.

Transitions between states are assumed to occur mid-interval and with a certain probability p_{ij}, which thus represents the probability that a scholar in state s_i at time t will transit to state s_j at time $t + 1$.

The defining property of a Markov chain is that the probability of moving to a future state depends only on the current state, and not on the sequence of past states, i.e., that:

$$P(Z_{t+1} = s_j \mid Z_t = s_i, Z_{t-1}, \ldots, Z_0) = P(Z_{t+1} = s_j \mid Z_t = s_i)$$

In other words, the process is memory-less, so that the transition probability depends only on the state at time t and not on the history before t.[12] Moreover, the Markov chain

[12] As discussed in depth by Shen and O'Donnell (2024), this Markov property can in some cases, including the one on career dynamics, be a strong assumption. Duration-dependent multi-state models, relaxing the memory-less assumption, might offer an alternative. Yet, Shen and O'Donnell (2024) show that, under certain conditions which also apply to our setting, standard multi-state models produce estimates closely aligned with more complex ones. We are thus reassured that our results are reliable even under the memory-less

is assumed to be homogeneous, so that transition probabilities do not change over time.

Hence, the one

$$P(Z_{t+1} = s_j \mid Z_t = s_i) = p_{ij}$$

and can be gathered in an $m \times m$ transition matrix, denoted with $P = \{p_{ij}\}_{i,j=1,\ldots,m}$ and structured as follows:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix}$$

where each element p_{ij} satisfies $p_{ij} \geq 0$ and $\sum_{j=1}^{m} p_{ij} = 1$ for all $i = 1, \ldots, m$.

This formulation allows for modeling the evolution of scholars' careers across academic stages as a stochastic process with memory-less transitions.

Recall that our dataset reports, for each scholar, the academic rank at the end of every calendar year from 2016 to 2021. This allows us to calculate the empirical transition probabilities between career stages from one year to the next. Since we have 6 years of observations, we actually derive one matrix P for each of the 5 periods, i.e., one based on the transitions occurred between 2016 and 2017, one for those occurred between 2017 and 2018, and so on.[13] The empirical transition probabilities are remarkably consistent across all five periods, thus strongly supporting the plausibility of the assumption that the Markov chain is homogeneous.

Given this setting, we are able to derive our two quantities of interest, namely: (i) the probability of visiting a certain state, conditional on starting from another one, in a given time horizon T, and (ii) the waiting time to first visit. In what follows, we briefly sketch how these quantities are derived based on the Markov chain presented above.

Waiting time to first visit a certain state s_j The expected waiting time to first entry is derived based on the probability distribution of the waiting time to first visit, which in turn is derived as described in what follows.

Consider a partition $\mathscr{A}$, $\mathscr{B}$ of the state space $\mathscr{S} = \{s_1, s_2, \ldots, s_m\}$ of the discrete-time Markov chain $\{Z_t\}_{t \geq 0}$, so that $\mathscr{A}$ and $\mathscr{B}$ are two disjoint subsets of the state space. In our setting, we may consider a partition that "aggregates" some of the $m = 8$ single possible states into career levels, namely: Tenured Researchers, Tenured Associate Professors, and Associate Professors, regardless of whether they are habilitated or not. This partition is instrumental to derive the waiting time to first visit of these career levels abstracting away from the additional steps required to qualify for the NSH.

Now let $P(V_t = v | Z_0 = s_i)$ denote the probability that the time required to visit the subset $\mathscr{A}$ (i.e. the process Z_t is in a state $s_j \in \mathscr{A}$) starting from state s_i is equal to v.[14]

Let $V(t, v) = \{P(V_t = v, Z_t = s_j | Z_0 = s_i)\}_{i,j}$ the matrix comprising the probability of having to wait v time units to enter in state $s_j \in \mathscr{A}$ conditional on starting in state s_i. Let $W(t, v) = \{P(V_t \geq v, Z_t = s_j | Z_0 = s_i)\}_{i,j}$ be instead the probability of waiting at

assumption.

[13]The 5 matrices are available in upon request.

[14]Note that, as is common in many social science applications Dudel (2021); Skoog and Ciecka (2010), we adopt the convention of assuming that transitions occur at the mid-interval.

least v units of time. Now for $v = 0$, the matrix W is:

$$W(t,0) = P^t$$

and for $v = 0.5$, the matrix W is

$$W(t,0.5) = \begin{pmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & P^t_{\mathscr{B}} \end{pmatrix}$$

where $\mathbf{0}$ is a matrix of zeros and $P^t_{\mathscr{B}}$ is the transition matrix with p_{ij} whose states s_i and s_j are both in $\mathscr{B}$. These identities, as well as the next one, follow from an equivalent derivation based on the time spent in the complementary subset $\mathscr{B}$. In fact, the probability of waiting at least v until entering the set $\mathscr{A}$ can be expressed as the probability that the process has remained in the complementary states $\mathscr{B}$ up to time t. See Dudel (2021) for further details. Consequently, for any other value of v the matrix W can be obtained as follows:

$$W(t,v) = \left[\begin{pmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & P^{v-0.5}_{\mathscr{B}} \end{pmatrix} \begin{pmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{1}_{m_{\mathscr{B}}} \end{pmatrix} \right]' \circ W(t,0.5)$$

where $\mathbf{1}_{m_{\mathscr{B}}}$ is a matrix of ones of the same dimension of $P_{\mathscr{B}}$, $'$ denotes the transpose and $\circ$ denotes the Hadamard product, i.e., the entry-wise matrix product.

Then, it follows that for $v = 0$

$$V(t,0) = W(t,0) - W(t,0.5)$$

and for any other value of v:

$$V(t,v) = W(t,v) - W(t,v+1)$$

Finally, the probability $P(V_t = v | Z_0 = s_i)$ can be obtained as the row sum of $V(t,v)$.

The expected waiting time to first visit is thus obtained as the expected value of this distribution computed up to a given horizon, which in our case is reasonably set to 40 years. Indeed, we consider 40 as the maximum value for the time horizon T given that academic staff in Italian universities are seldom appointed before the age of 30 and are legally required to retire at 70. Consequently, a 40-year period effectively encompasses the full length of an academic career. This is empirically supported by the distribution of academic age, computed as the number of years elapsed since the first publication and illustrated in Figure 2. Note that, the expected waiting time to first visit that we derive represents the average time required for an individual in state s_i in year t to visit state s_j, regardless for the time (already) spent in state s_i (and not as the time taken to transition from i to j once they have reached state i).[15]

[15]Recalling that our dataset spans the years between 2016 and 2021, this quantity is derived separately for each of the 5 periods and their average is used instead for the results presented in the paper. Results for each of the 5 years are available upon request.

Probability of visiting a certain state s_j in a given time horizon T We want now to focus on the probability of visiting a certain state. In classical Markov chain theory, the probability of visiting a given state is typically defined as the probability of ever reaching that state, under the assumption of an infinite time horizon (see, e.g., Kemeny and Snell (1983)). This formulation is appropriate in theoretical settings or in applications where the temporal dimension is abstract or unbounded. However, in the present context such an assumption is not meaningful. The Markov chain considered here represents annual career transitions, and its states correspond to academic positions held by individuals over the course of their working life. Since academic careers are finite in time, constrained by retirement or mortality, allowing the chain to evolve indefinitely would produce a quantity with no empirical interpretation.

Moreover, when applying the classical definition to this empirical setting, the resulting probability of ever reaching a given state tends to approach one, particularly because the states in the model communicate and, under an infinite time horizon, the chain will likely reach the target state. For this reason, instead of relying on the asymptotic probability of ever visiting a state, we prefer to compute the probability of reaching the target state within a fixed time horizon. Computationally, this probability is obtained by summing the probability mass function of the first-passage time up to the chosen horizon T, that is, by summing up the probabilities of first visiting the state in $v = 1, 2, .., T$ steps. Denoting by $H(T|Z_0 = s_i)$ such a probability we have

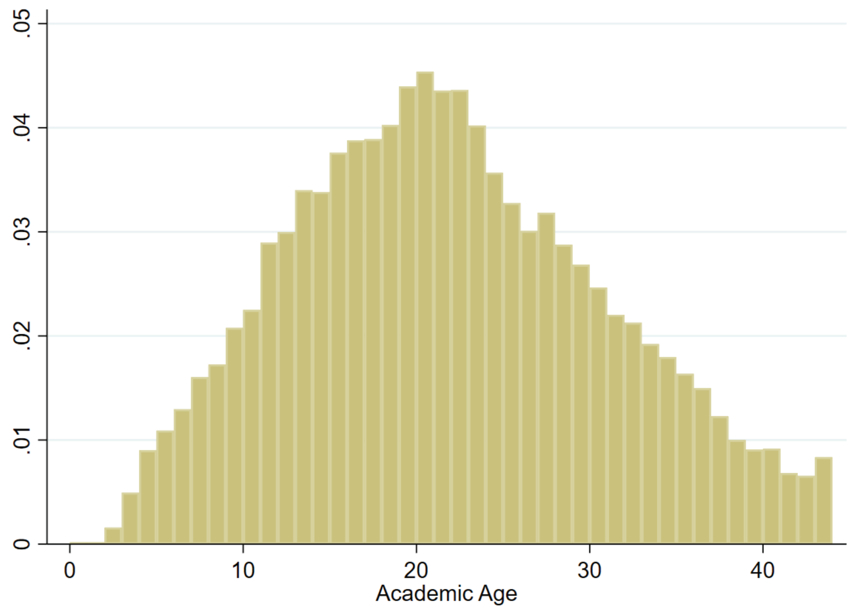
$$H(T|Z_0 = s_i) = \sum_{v=1}^{T} P(V_t = v|Z_0 = s_i).$$

This quantity is therefore both theoretically coherent with the structure of the model and empirically interpretable in the context of finite working lives.

In our application, the maximum value for the career horizon T is set to 40, as recalled above. Besides, the results in terms of transition probabilities will be presented also referred to shorter career horizons, namely $T = 10, 20, 30$ and 40.

Both the time to first visit and the probabilities of visiting the state of Full professor are retrieved separately for the subgroups of scholars of interest. First, we compute them for male and female scholars, so as to assess potential gaps along the gender dimension. It is worth recalling that we focus on the transitions of scholars qualified with the NSH only, so that what we get is an assessment of the gender gap net of the argument that women tend to shy away from competition. Next, we compute these quantities for the 4 subsets of scholars based on their quartile of scientific productivity. This is done to check whether scholars with different levels of scientific productivity actually face different probabilities and time of career advancement. Finally, we compute all quantities of interest distinguishing by both gender and quartile of productivity (i.e., male scholars having qualified with NSH and with an h index in Q1, i.e. in the first quartile of the sector-specific distribution, NHS-qualified male scholars in Q2, ... , females in Q1, females in Q2), so as to assess whether gender gaps exist even once we control for the degree of scientific productivity.

Figure 2: Empirical distribution of academic age



Note: Academic age is computed as the years passed between 2021 and the year of first publication.

5 Results

5.1 Baseline Results

Table 3 reports the average probability of visiting the state of Full Professor considering 4 different time horizons, from 10 to 40 years, and three different initial states, namely TR, TAP and AP, all considered with habilitation [16]. Figure 3 provides a graphical representation of the same probabilities to ease the reading of the results. Two considerations are in order. First, recall that the transition from AP to FP may occur in a single step, whereas the transition from TR or TAP requires two or more steps. This explains why the probability of eventually reaching the top academic rank is higher for APs, ranging from 72.3% to 93.2% depending on the time horizon, than for the two more junior ranks, for which it ranges from approximately 30% to 87%. Second, regardless for the initial state, the probability of reaching the Full professorship increases with the horizon, meaning that the wider the potential career horizon, the higher the likelihood that scholar will eventually become a full professor. Both these results are consistent with expectations and real world dynamics that the chain aims to catch.

We then explore how the probability of reaching the highest academic position varies with the level of scientific productivity by using the h index to classify scholars.

The results are reported in Figure 4, for each of the three potential initial states considered. The results obtained are again in line with expectations. If, on the one hand, the probability is confirmed to increase with the career horizon, on the other hand, we

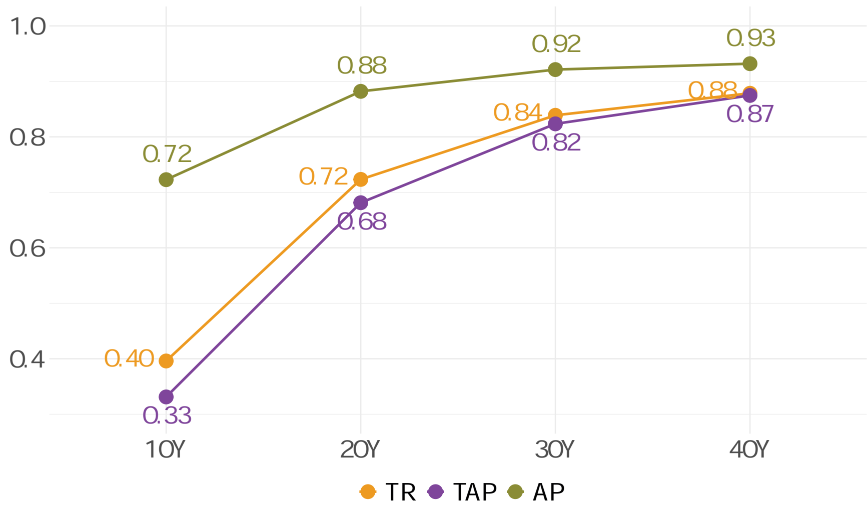
[16] In the following, we drop the subscript $_H$ for simplicity of notation.

Table 3: Probability of visiting the state of Full Professor

Career Horizon	Tenured Researcher TR_H	Tenure-track Assistant TAP_H	Associate AP_H
10 Years	0.396	0.331	0.723
20 Years	0.723	0.681	0.882
30 Years	0.839	0.823	0.921
40 Years	0.879	0.875	0.932

The Table reports the average probability of visiting the state of Full professor, by career horizon $T = 10, 20, 30, 40$ and starting career level. The starting career levels are TR_H, Tenured Researcher Habilitate with the NSH for Associate Professor, TAP_H, Tenure-Track Associate Professor Habilitate with the NSH for Associate Professor, and AP_H, Associate Professor Habilitate with the NSH for Full Professor.

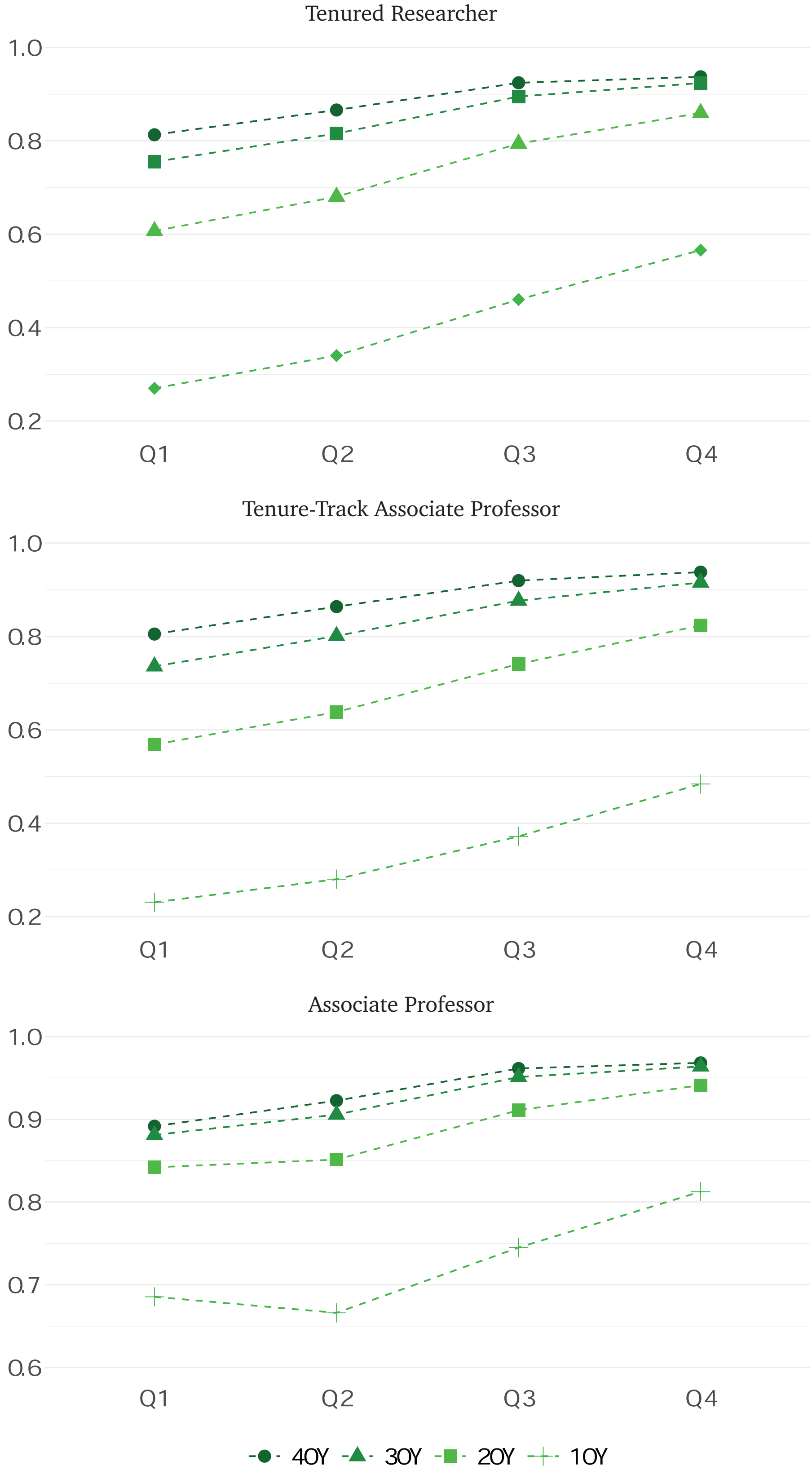
Figure 3: Probability of visiting the state of Full professor, by time horizon and initial state



find that it also progressively increases with the level of productivity. In other words, the more productive a scholar is, the more likely s/he will get promoted to Full professor. We can thus affirm that the Italian university system rewards those whose scientific productivity is higher. This evidence is confirmed for each of the three potential initial states.

Finally, leveraging our methodology, we can extract the average time to the first visit. Recall that in this case we focus on the 40-year horizon only. Table 4 reports the results obtained by initial state and level of productivity and Figure 5 graphically represents them. We find that, on average, regardless for the years spent in the current position, it takes 15.20 (16.15) years to reach the state of Full professor for a Tenured Researcher in the first quartile of their sector-specific distribution of scientific productivity and 16.15 years for a Tenure-track Associate Professor in the equivalent position. The equivalent measure for an Associate Professor in the equivalent position in the distribution is 6.83 for Associate Professors (in Q1). These results mirror those obtained for the probability

Figure 4: Probability of reaching Full professorship, by productivity, career horizons and initial state



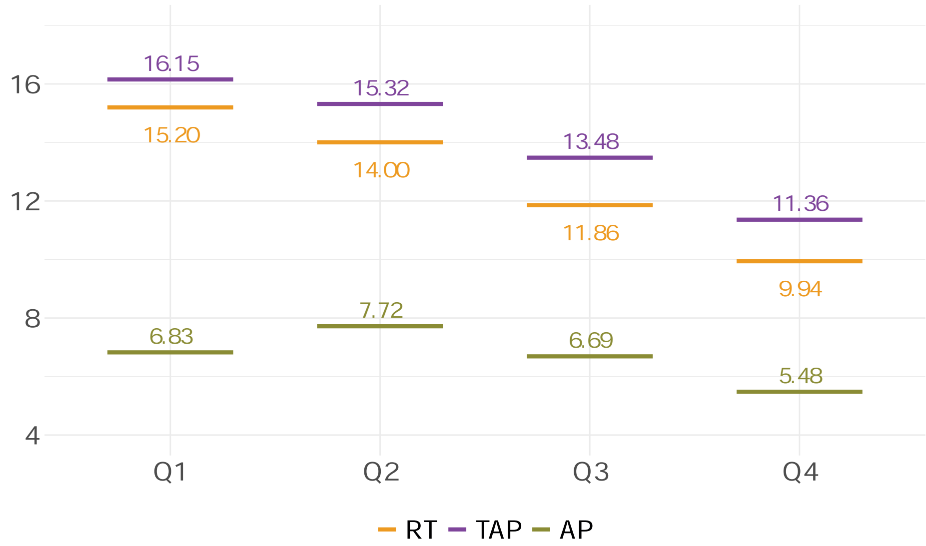
of visit, as the average time of first visit to the state of Full Professor is shorter for Associate Professors compared to the two junior figures.

Table 4: Time to reach Full Professorship, over a 40-year career horizon

Productivity Level	Tenured Researcher TR_H	Tenure-track Assistant TAP_H	Associate AP_H
Q1	15.20	16.15	6.83
Q2	14.00	15.32	7.72
Q3	11.86	13.48	6.69
Q4	9.94	11.36	5.48

The Table reports the average time to firs visit of the state of Full professor considering a career horizon $T = 40$, by scientific productivity level. The starting career levels are TR_H, Tenured Researcher Habilitate with the NSH for Associate Professor, TAP_H, Tenure-Track Associate Professor Habilitate with the NSH for Associate Professor, and AP_H, Associate Professor Habilitate with the NSH for Full Professor.

Figure 5: Time to reach the state of Full professor, by level of productivity and initial state



Moreover, regardless of the current career stage, the time to reach the state of Full Professor reduces when the level of scientific productivity is higher.

In other words, the career progressions of the scholars working in the Italian Academic system co-move with the level of scientific productivity: the higher the level of scientific productivity, the higher the probability and the shorter the time need to reach the highest career level.

5.2 The Gender Gap

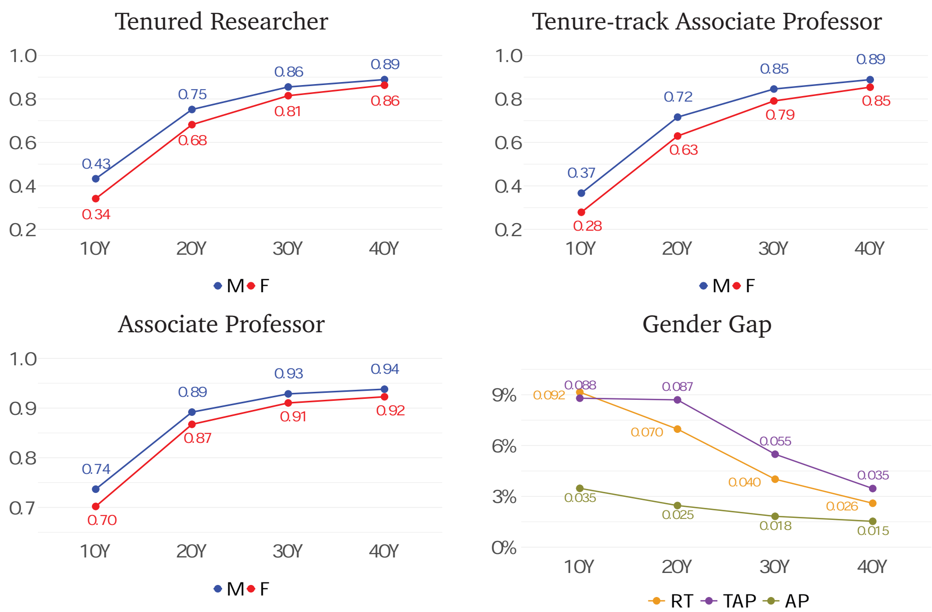
We now move to the investigation of potential gaps in the two quantities of interest in terms of gender.

We thus repeat the analysis above distinguishing male from female scholars. The first three graphs reported in Figure 6 graphically represent the probabilities of visiting the state of Full professor for males (in blue) and female (in red) scholars, once again at the different career horizons considered above, $T = 10, 20, 30, 40$ years and for each of the three potential initial states, namely TR, TAP and AP. Regardless of the initial state and the career horizon considered, the probability of reaching the highest career level is systematically higher for male scholars compared to their female counterparts.

The bottom-right panel of Figure 6 pictures the gender gap in the probabilities, by career horizon and initial state and shows that this gap never completely vanishes. Indeed, despite it progressively reduces along the time horizons considered, starting from about 8.8 percentage points for TR and from 3.5 for AP, it never reaches zero, stabilizing between 1.5% (the lowest for AP) and 3.5% (the highest for TAP). We can further observe that TAP, to be compared with TR, is the position experiencing the most severe gap.

Notice that these final estimates of the gender gap are remarkably in line with the one reported in the literature for the Italian case, by, e.g. Filandri and Pasqua (2021); Brunetti et al. (2023, 2024) and Iaria et al. (2022), whose analyses are not able to provide a dissection of this gap over the career horizon.

Figure 6: Probability of visiting the state of Full professor, by productivity, time horizons and initial state



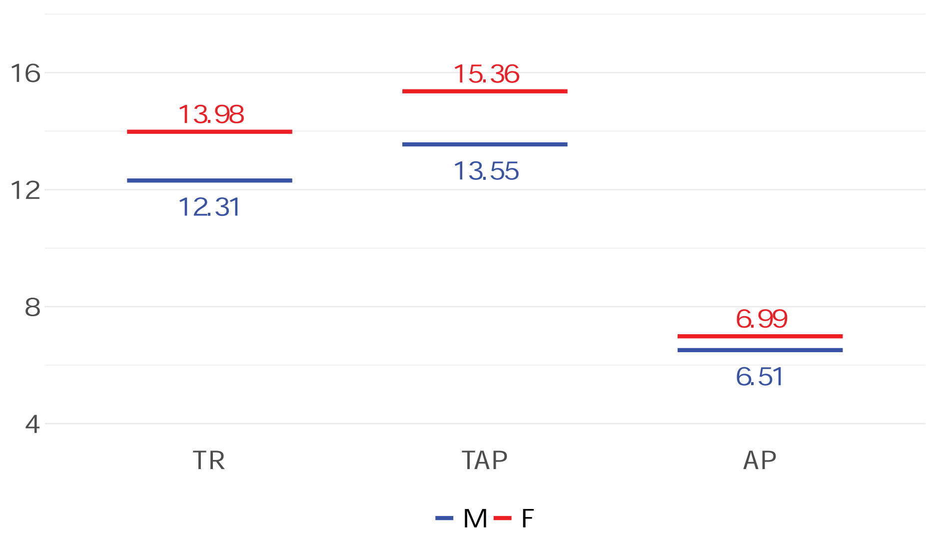
5.3 A new Gender Gap: the Pink Queue

We now turn our attention to the time of first visit, again in a gender perspective. Recall that in this case, the results refer to the time of first visit computed over the 40-year horizon, i.e., the longest career horizon considered. This is done for two reasons. First, it allows the estimation of these probabilities once the Markov Chain is allowed to run over the entire career horizon. Second, as shown above, the results referring to the 40-year horizon are the most conservative one, so that for the other horizons the results (available upon request) hold even more.

Figure 7, reports a graphical representation of the time of first visit of the state Full professor, by gender of the scholar and initial states. Regardless of the scholars beginning their career as TR, TAP or as AP, our results show that the time required to achieve the Full professorship is always higher for females scholars than for males ones. In particular, female scholars wait up to 2 years longer than their male scientific-comparable counterparts.

In other words, our results not only confirm the classical gender gap in terms of probability, i.e., that female scholars have a lower probability of reaching the highest career level than their male counterparts, but also that it also takes longer time (up to 2 years more, depending on the initial state) for women to achieve this result. We refer to this result as "pink queue", as it seems to suggest that somehow female scholars are “postponed”, making women wait longer to get a career advancement.

Figure 7: Time of first visit, by initial state and gender



5.4 Double Standard

After identifying a gender gap both in terms of probability and in terms of time to achieve a certain career stage, we aim to consider the factor of productivity. The productivity puzzle is commonly cited as a rationale for the gender gap, although much literature has demonstrated that the gap persists even when accounting for individuals' scientific productivity (see, e.g., Baker (2012), Bosquet et al. (2019b), Iaria et al. (2022) and Filandri and Pasqua (2021), Brunetti et al. (2023), specifically for the Italian case).

We thus repeated the analysis of the gender gap for each quartile of scientific productivity, recalculating the transition matrices and estimating the probabilities of visiting the state of Full professor within 10 to 40 years. The results for the probability of visiting the state of Full professor are illustrated in Figures 8 when the initial position considered is TR, in 9 when the initial position is TAP and in 10 when the initial position is AP.

Figure 8: Probability of visiting the state of Full professor starting from Tenured Researcher, by h index quartile and career horizon

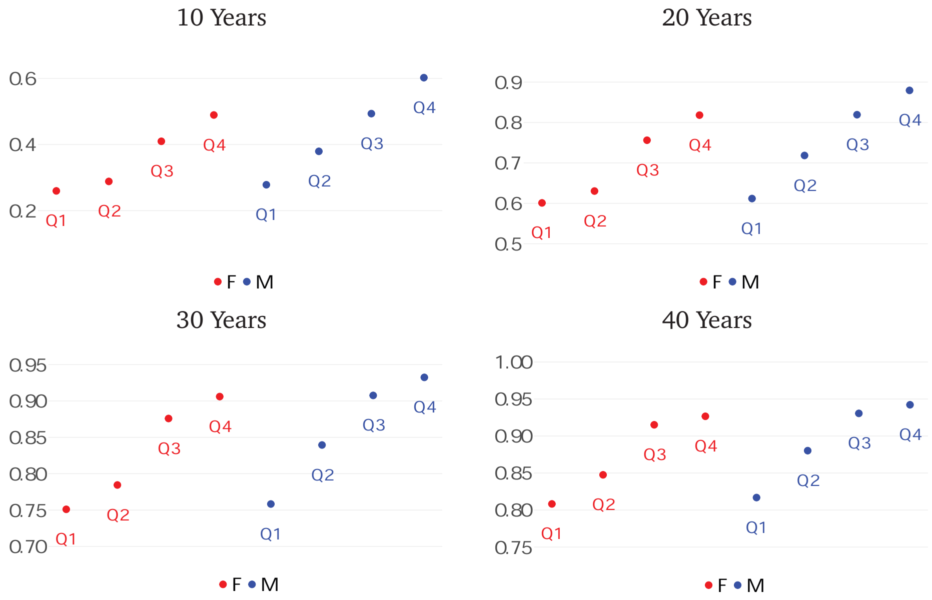


Figure 9: Probability of visiting the state of Full professor starting from Tenure-Track Associate Professor, by h index quartile and career horizon

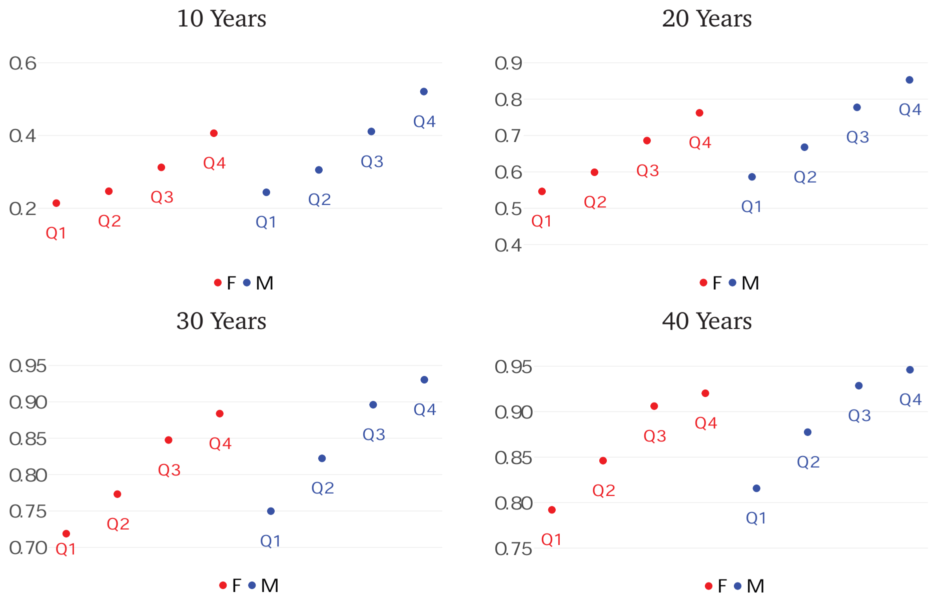
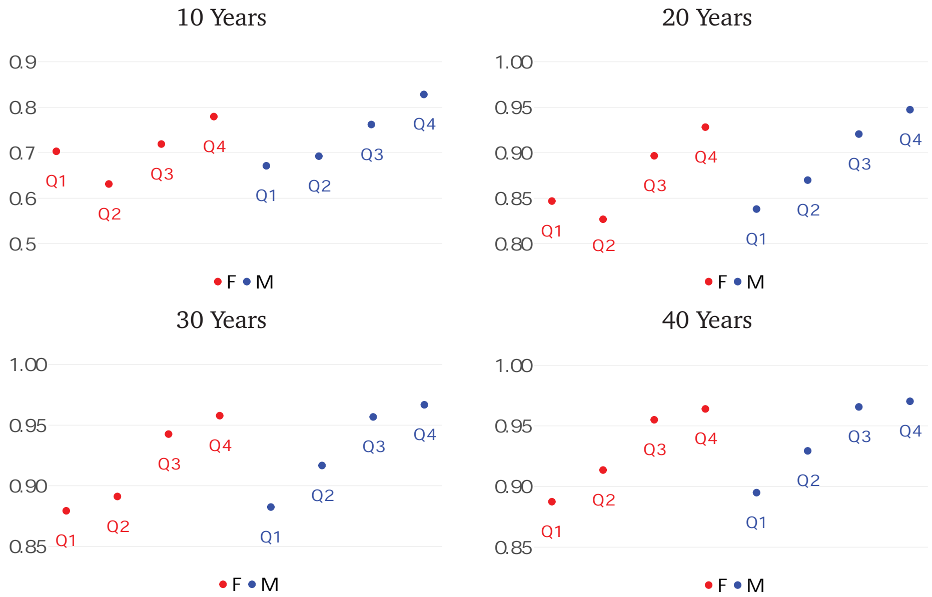


Figure 10: Probability of visiting the state of Full starting from Associate, by h index quartile and time horizon



For both genders, the probability of reaching the top academic position progressively increases with the level of productivity, thus confirming the evidence found in the baseline case. However, we observe a systematic misalignment between the probabilities of male and female scholars of the same productivity level. Take, for example, the first panel of Figure 8. It shows that the likelihood of becoming a full professor for female TR in the top quartile of the h index distribution is 49%. This probability is basically equivalent to the chances estimated for males in the third quartile of the distribution, also equivalent to 49%, while the corresponding probability (i.e., the one for male TRs in the top quartile) is 60%, with a gap almost reaching as much as 11 percentage points. Similarly, the probability for female TRs in the third quartile is 41%, aligned to the 38% estimated for male in the second quartile of the distribution, with a gap with male scholars in the corresponding quartile of about 8 percentage points. This misalignment is systematically observed for all quartiles of scientific productivity and across all time horizons considered, with gender gaps ranging between 1 and 11 percentage points for TR, and between 2 and 11 percentage points for TAP. The case of AP is the one where the observed gaps are the lowest in magnitude and the only one in which we find an exception. Indeed, our estimates show that the chances of being promoted to Full professor for AP women below the median of scientific productivity are 1 to 3 percentage points *higher* than the corresponding figures for AP men. Yet, all other combinations of career horizons and productivity level display a gender gap in favor of male scholars, which - even if lower than the one reported for younger figures, still reaches up to 5 percentage points.

These gaps typically increase with the level of productivity and decrease with the career horizons considered, consistently with the baseline results. For instance, the lowest gap for TR and TAP (AP), around 2-3 (1) percentage points, is found over the

40-year horizon and between scholars in the lowest quartile of the productivity. The corresponding figures over the 10-year horizon and between scholars in the top quartile of scientific productivity are as much as 5 times higher.

We refer to this systematic misalignment between the probabilities of male and female scholars of the same productivity level as “double standard”, since it seems to suggest that women must achieve higher standards with respect to men in order to get to the same career level.

Figure 11 reports the corresponding results for the time to first visit. Once again we find that the Italian University rewards the scientific productivity, as the time to first visit reduces the higher is the quartile of productivity. However, female scholars of any given quartile are systematically found to wait up to 2 years more than their male counterparts, regardless of the initial state, whether TR, TAP or AP (with the sole exception of Associate female professors in the lowest scientific productivity quartile, for whom we estimate a *shorter* time to first visit of half a year).

Hence, we conclude that the double standard is observed not only in terms of probability, but also in terms of time to first visit; furthermore what we call pink queue is confirmed also to appear when productivity is considered.

6 Further Results

In this Section we provide additional results, with the aim to investigate whether the evidence found varies with the cohort of the scholars or with their academic age, both determined based on the year of first publication. [17]

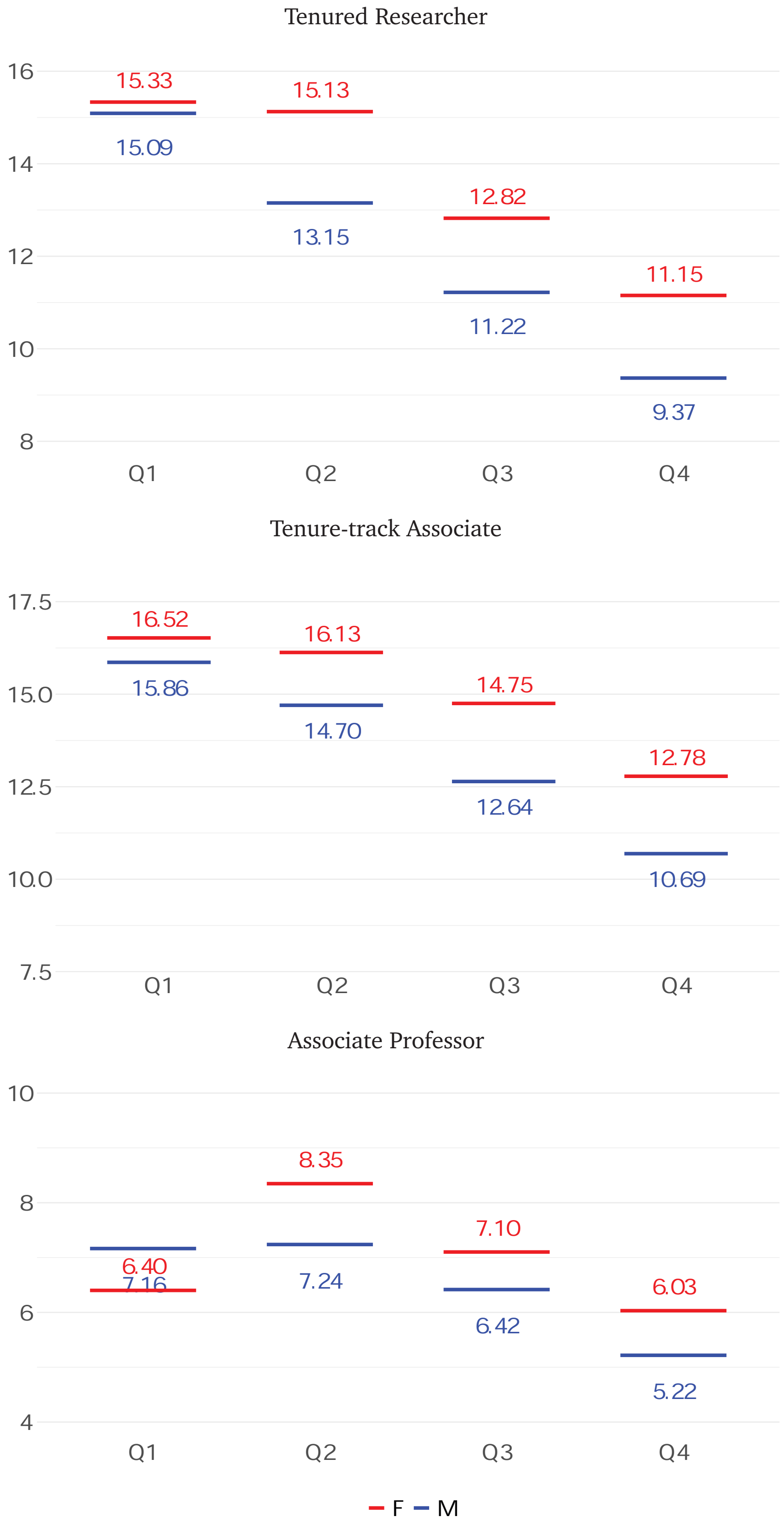
6.1 Cohort

The Italian higher education system has been reshaped several times during the last decades. The two major reforms occurred are the so-called Zecchino reform (approved in 1999) and the Gelmini reform (approved in 2010). The former introduced the so-called “3+2” structure, aligning Italy with the Bologna Process and dividing university studies into a three-year undergraduate degree followed by a two-year master’s degree. This reform not only altered the timing of entry into the academic job market but also reshaped the pool of potential doctoral candidates by increasing both the number and heterogeneity of graduates. In contrast, the Gelmini reform focused on governance, recruitment, and evaluation. It imposed stricter rules on academic hiring, introduced performance-based funding mechanisms, and emphasized research productivity as a criterion for career progression. Together, these reforms significantly affected the demographic composition of academic cohorts and the trajectory of academic careers, creating potential discontinuities that might affect the results obtained in the empirical analyses of productivity and career advancement.

We thus replicate the analysis across different cohorts. In order to do so, we leverage on the year of the first publication present in our dataset to sort each scholar into

[17] We also repeat the analysis on the subsample of 20369 scholars belonging to bibliometric sectors only. Results, available upon request, are remarkably robust.

Figure 11: Time of first visit of Full professor, by initial state and gender



one of the following three generational groups, whose cutoff exactly replicate the occurrence of the two major reforms cited above, namely: 1980–1999, 2000–2009, and 2010 onward. We label the first cohort "Gen B", as "Boomers", as those publishing their first academic paper in the 1980s are likely to be born around the 1960s. We label the second cohort "Gen X", as those having published their first paper in the first decade of the new century are likely to be born in the 1970s. The last generation gathers those having published their first paper after the 2010, i.e., those born after 1980s, and are thus labeled as "Gen M", after "Millenials".

The sample distribution by gender, cohort and productivity level is reported in Table 5 and reveals marked imbalances. The youngest generation, the one of the Millenials, is by construction dominated by individuals who are still at an early stage of their academic career. As a consequence, only few of them have reached the top quartile of scientific productivity (457 male, 291 female). This subgroup is thus numerically too small to allow meaningful inference, as its career trajectories cannot be reliably mapped onto the full academic hierarchy.

Table 5: Number of scholars in the sample, by gender, cohort and scientific productivity level

Productivity	Gen B		Gen X		Gen M		Total
Level	M	F	M	F	M	F	
Q1	1050	783	2115	1643	2071	1763	9425
Q2	1321	1048	1863	1356	891	697	7176
Q3	1721	1072	1693	1081	651	528	6746
Q4	2410	1088	1742	795	457	291	6783
Tot	6502	3991	7413	4875	4070	3269	30130

The Table reports the number of scholars in the sample, by scientific productivity level, gender and cohort. Cohort are defined based on the year of first publication: "Gen B" represents scholars having published their first academic paper in the 1980s, "Gen X" are those having published their first paper in the first decade of the new century, and "Gen M" those having published their first paper after 2010. Productivity level refers to the quartile of the distribution of the sector-specific h index to which the scholar belongs. Q1 denotes the first quartile, Q2, the second, Q3, the third and Q4 the the best 25% scholars, in terms of sector-specific scientific productivity.

Moreover, while both male and female scholars are significancy represented in the first two cohorts, in the Millenials' one the gender unbalance is even stronger, with a pronounced male dominance. The introduction of fixed-term positions by the Gelmini reform has exacerbated job uncertainty and performance pressures, which notably disproportionately affect women. This has contributed to reinforce the well-known *leaky pipeline* phenomenon in Italian academia: at early career stages, women disproportionately exit or are filtered out, limiting their progression to permanent roles and contributing to persistent vertical segregation later in the career path (see, Falco et al. (2023); Bozzon et al. (2017)).

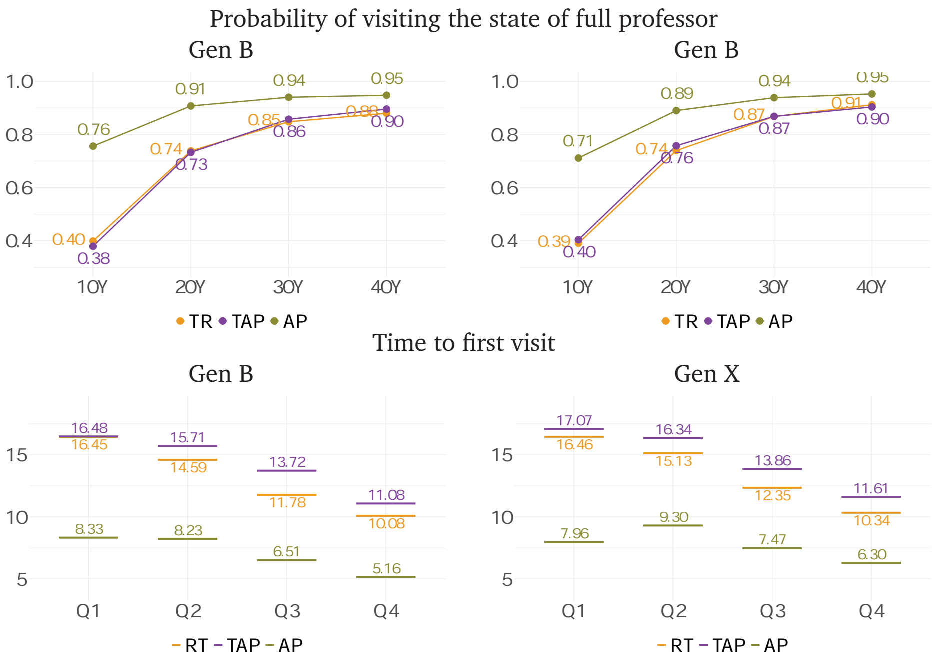
For the above reasons, we will focus on Gen B and Gen M only, where both sample size and career maturity allow a robust comparison.

Figure 12 reports the baseline results for two generations, and confirms the evidence reported over the full sample, with no remarkable differences between the two cohorts.

In both cases in fact we observe that the probability of (time required for) achieving Full professorship is higher (lower) for Associate Professors, increases (decreases) with productivity, and is higher the longer the career horizon.

Looking at the gender gaps, Table 6 reports the estimated average probability of visiting as well as the time to first visit of the state of Full professor, by gender and generation. The corresponding gender gap is pictured in Figure 13 for an easier reading of the results and shows that the gender gap in the probability of visit the state of Full professor follows the same dynamics observed in the main results: it reduces the longer is the career horizon, but it never vanishes. Moreover, it shows that it is more marked in Gen X rather than in Gen B. Similarly, the analysis of time to first visit confirms the main evidence, signaling the presence of a comparable "pink queue" in both generations (see Figure 14).

Figure 12: Baseline results, by generation



Finally, controlling for productivity, we observe for both generations the same systematic misalignment between the results for male and female scholars of the same productivity level, both in terms of probability of visiting the state of Full professor (see Figures 15 for TR, 16 for TAP, and 17 for AP), and of time to first visit (see Figure 18).

We thus conclude that the “double standard” is present in both generations.

Figure 13: Probability of reaching Full professorship: gender gap, by career horizons, generations and initial state

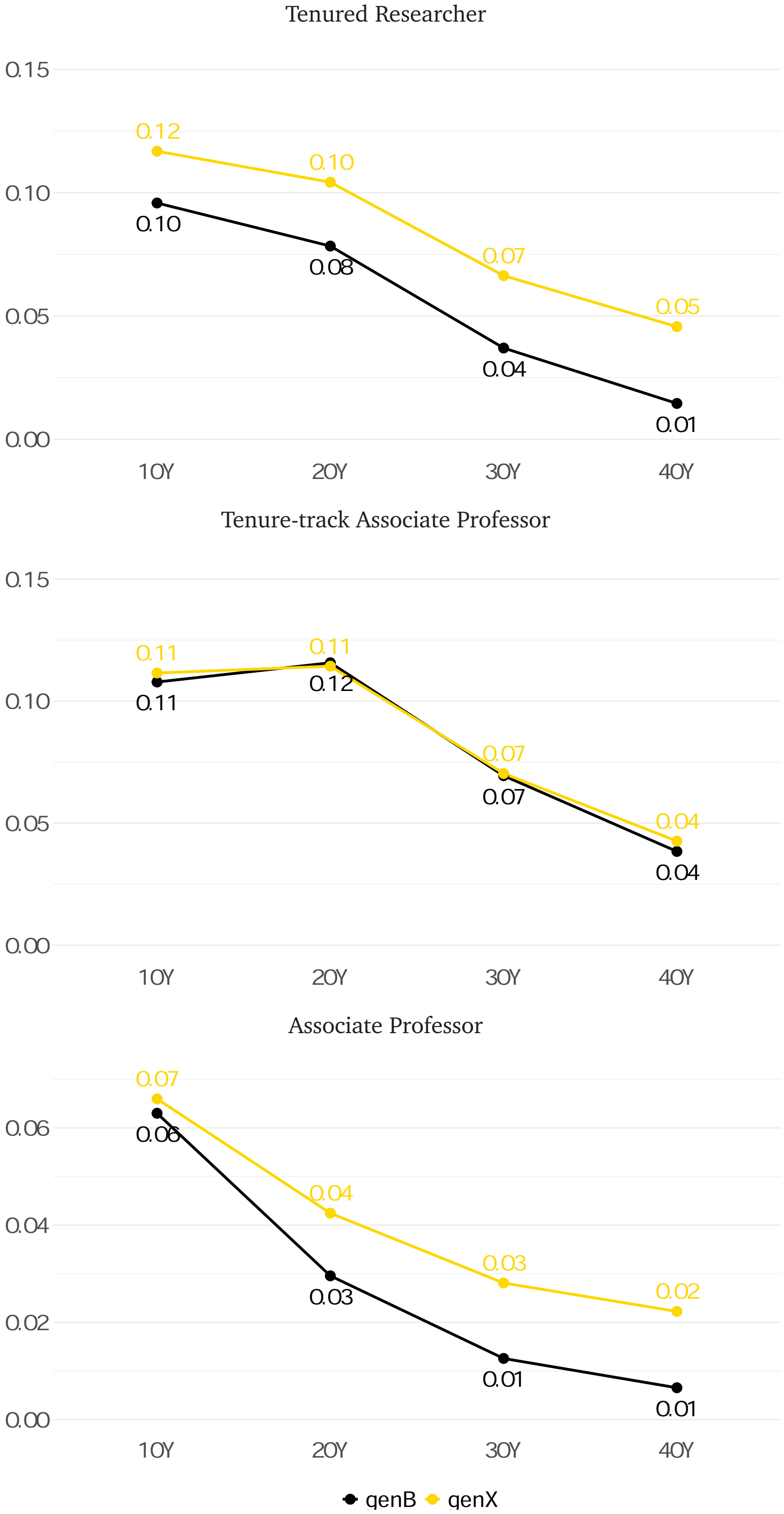


Figure 14: Pink queue: time to first visit by gender and generation

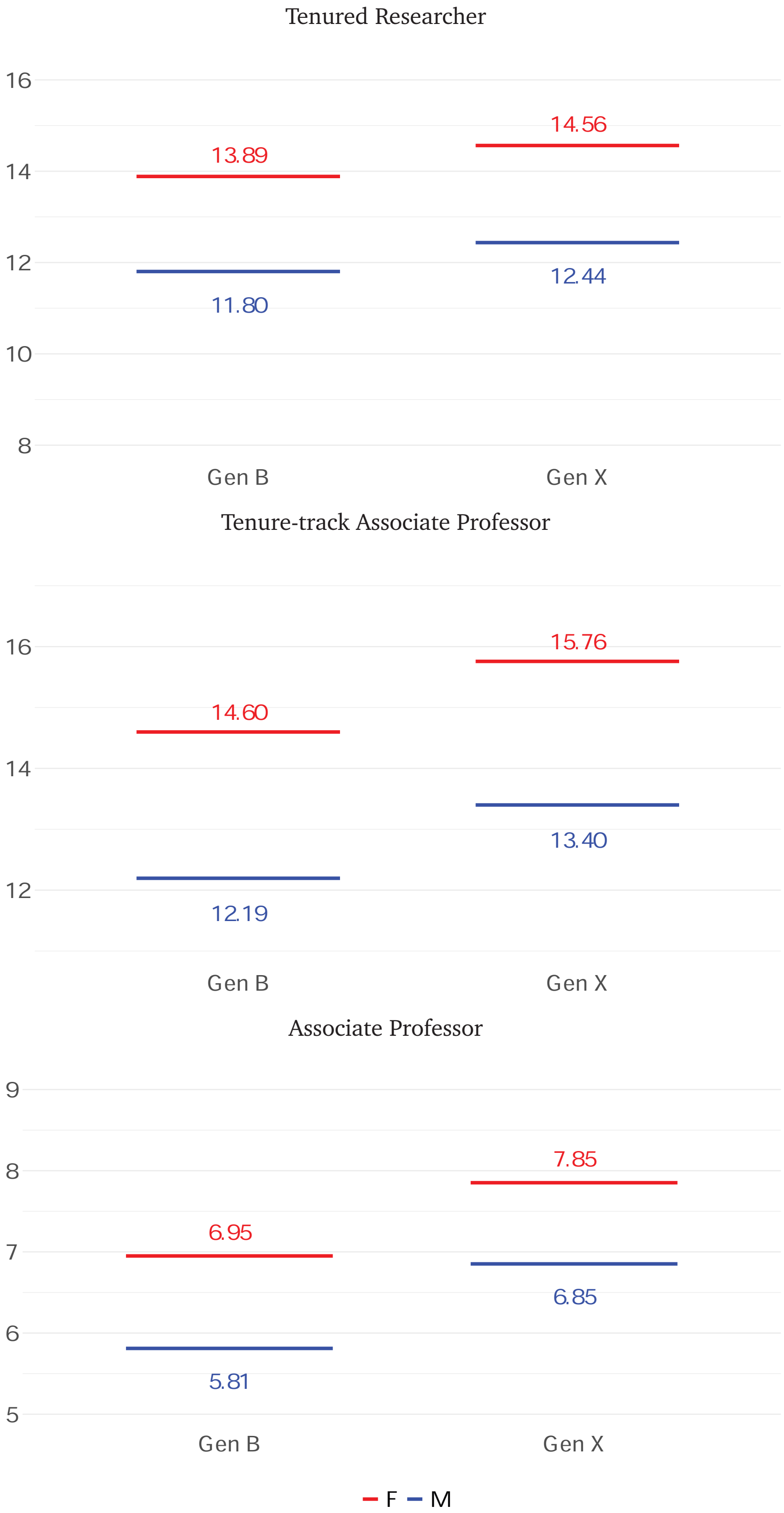


Figure 15: Double standard for Tenured Researchers: probability of first visit under different horizon and different level of productivity by gender and generation

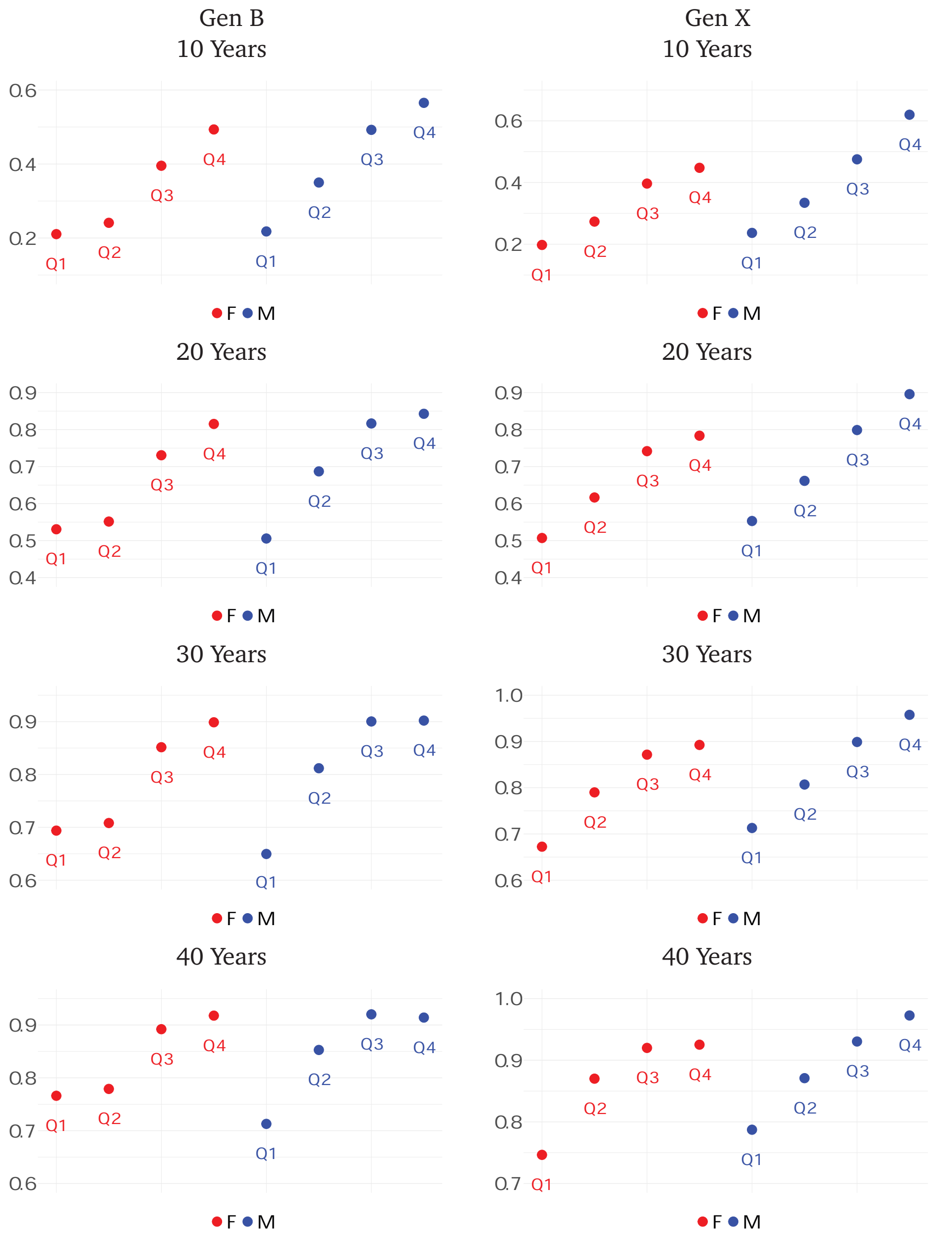


Figure 16: Double standard for Tenure-track Associate Professors: probability of first visit under different horizon and different level of productivity by gender and generation

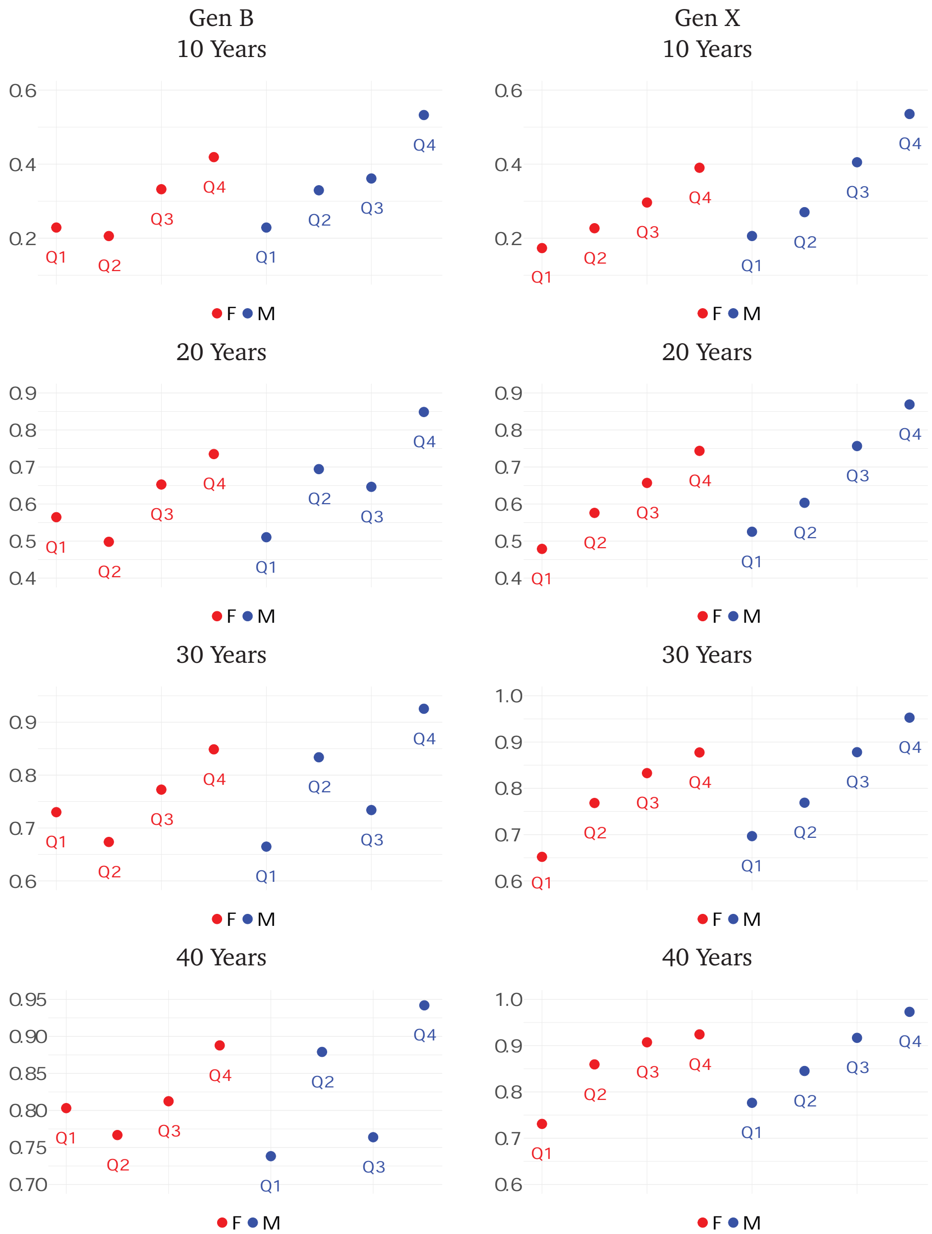


Figure 17: Double standard for Associate Professors: probability of first visit under different horizon and different level of productivity by gender and generation

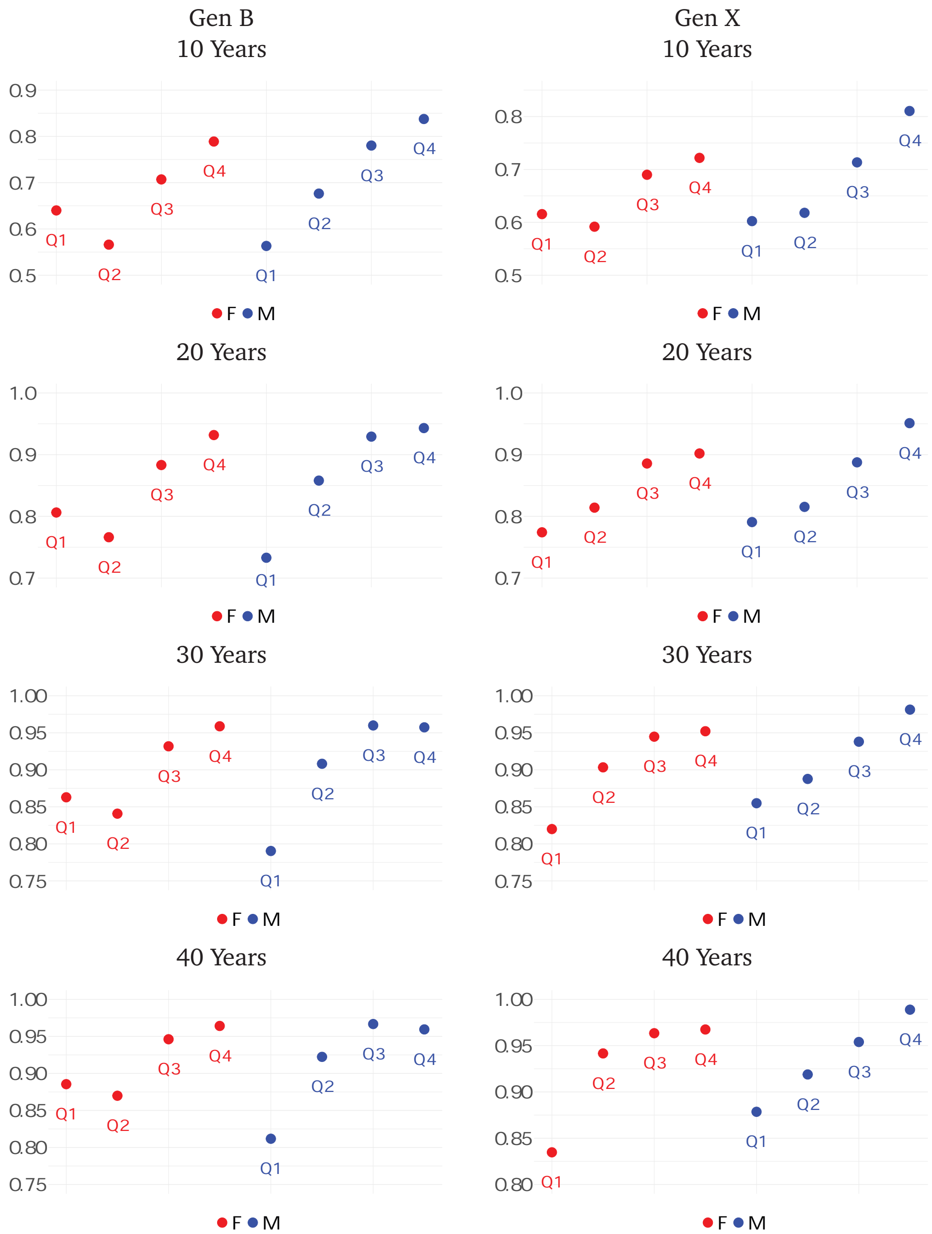


Table 6: Reaching Full professorship: probabilities by career horizon and time to first visit, by gender, generation, and starting state

		Gen B				
From	Gender	10 years	20 years	30 years	40 years	Time of first visit
TR_H	M	0.435	0.768	0.862	0.885	11.804
	F	0.340	0.690	0.825	0.871	13.886
TAP_H	M	0.420	0.777	0.883	0.910	12.195
	F	0.313	0.661	0.814	0.871	14.598
AP_H	M	0.780	0.918	0.944	0.950	5.811
	F	0.717	0.889	0.932	0.943	6.950
		Gen X				
From	Gender	10 years	20 years	30 years	40 years	Time of first visit
TR_H	M	0.435	0.779	0.893	0.929	12.437
	F	0.318	0.675	0.826	0.883	14.563
TAP_H	M	0.376	0.742	0.875	0.918	13.399
	F	0.265	0.628	0.805	0.875	15.757
AP_H	M	0.736	0.906	0.949	0.961	6.852
	F	0.670	0.863	0.921	0.938	7.852

The Table reports the probability of visiting the state of Full professor, by career horizon $T = 10, 20, 30, 40$, and the time to first visit considering the horizon $T = 40$, by starting state, gender and cohort of the scholar. The starting states considered are TR_H, Tenured Researcher Habilitate with the NSH for Associate Professor, TAP_H, Tenure-Track Associate Professor Habilitate with the NSH for Associate Professor, and AP_H, Associate Professor Habilitate with the NSH for Full Professor.

6.2 Academic age

In this section, we take into account heterogeneity in terms of seniority in the Italian academia. To this end, we modify the Markov chain in order to consider the academic age of scholars, whereby the academic age is defined as the time between the year of first publication and the current year. In our application, we grouped academic ages into three categories, namely: (i) Junior, with less than 10 years of academic career, (ii) Advanced, with academic career comprised between 11 and 20 years, and (iii) Senior, with over 20 years of academic career. Each state of the Markov chain is thus tripled, assuming that each career position can be visited in each of these three stages of the academic career. The resulting Markov chain thus counts 22 potential states, 21 transient states (i.e., the original 7×3) and 1 absorbing state. In this case, the metrics are computed such that the probabilities and the timing of visit for FP take into account the entire triplet, i.e., either FP_{Junior}, $FP_{Advanced}$, or FP_{Senior}.

In this setting, the transition probability matrix becomes a block diagonal matrix. Indeed, considering an academic age from 0 to T (whereby we assume $T \leq 40$, as above) the probability transition matrix becomes:

$$P = \begin{pmatrix} P_0 & \mathbf{0} & .. & .. \\ \mathbf{0} & P_1 & \mathbf{0} & .. \\ \vdots & & \ddots & \end{pmatrix}$$

where P_x is a 8×8 matrix, reporting the transition probability from a state s_i at age x

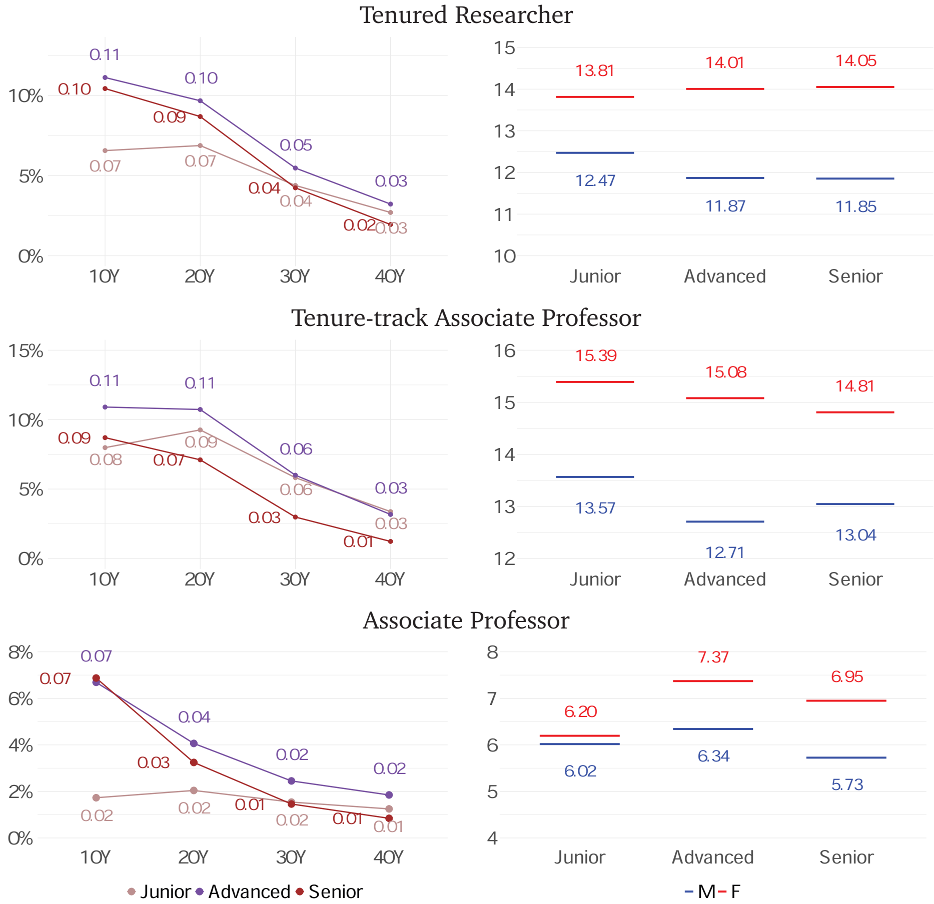
Figure 18: Time of first visit of the state of Full professor at 40 years horizon, by initial state, gender and generation

to state s_j at age $x+1$).

Results for this analysis are graphically summarized in Figure 19. The panels on the left-hand side report the difference between the estimated probability of visiting the state of Full professor between male and female scholars, by academic age (Junior, Advanced, and Senior) and by initial state considered (TR, TAP and AP). Also in this case, in all cases considered, we confirm the presence of a gender gap. For instance, female Junior Tenured Researcher have a chance of visiting the state of Full professors over a 10-year horizon which is 6.6 percentage points lower than their male counterparts. This gap reaches more than 10 percentage points when we consider Tenured Researchers who are in a more advanced state of their career. Similar gaps (between 8 and 11 percentage points) are found for TAPs over the same 10-year career horizon. Finally, for APs, we find a gender gap in the probability of reaching the highest career level which is around 2 percentage points for Junior scholars and around 7 percentage points for scholars in a more advanced state of their career. Consistently with the baseline results, the gaps tend to reduce over the career horizon, but not never completely vanish, remaining around 2-3 percentage points when the 40-year career horizon is considered.

The panels on the right-hand side of Figure 19 picture the estimated time to first visit for male and female scholars, again by academic age and initial state considered, and once again confirms the presence of a systematic pink queue, which - with the only exception of Junior AP, for which it is negligible - is stable around 2 years.

Figure 19: Gender Gap and Pink queue, by current career stage



7 Concluding Remarks

We examine gender gaps in academic career progression by applying, for the first time in this context, a discrete-time Markov multi-state model. We use Italy as a case study, as its institutional specificity provides an ideal empirical setting for assessing gender gaps net of the most common confounders emphasized in the literature, such as differences in preferences for competition, work–life balance constraints, and/or different level of scientific productivity. We leverage a uniquely rich dataset, suitably generated for this analysis based on three different data sources. The dataset maps all career progressions occurred in the Italian Universities over the 6-years period spanning 2016-2021 (5 transitions). Besides, for each scholar it also provides detailed information on the National Scientific Habilitation(s) (NSH) s/he has achieved, as well as with his/her scientific productivity, as measured by the h index. Using this framework, we derived two sets of core quantities, namely the probability of and the expected time for reaching the rank of Full Professor. In order to assess potential gender gaps, these metrics are computed for male and female scholars, separately.

Our empirical analysis yields several key results. First, consistent with existing evidence, women face systematically lower probabilities of reaching the highest academic rank. This gap emerges across all current positions considered, i.e., the entry positions of Tenured Researcher (TR) and Tenure-track Associate Professor (TAP), as well as for Associate Professor (AP), reduces with time, but never vanishes. For example, over a 10-year career horizon, the gender gap in the probability of reaching Full Professor is approximately 9 percentage points for scholars being in entry positions, and around 4 percentage points for those being AP. When a 40-year horizon is considered, which approximates a full academic career, the gap reduces but does not disappear, remaining at roughly 2–3 percentage points depending on the current career level. These results reveal a persistent structural disadvantage for women, consistent with broader patterns documented in the literature (Iaria et al. (2022), Filandri and Pasqua (2021) and Brunetti et al. (2023)).

Second, we provide evidence that gender differences are not confined to promotion probabilities but extend to the timing of promotions as well. On average, female scholars need one to two more years than male scholars to reach Full Professorship, conditional on starting from the same position, being NSH-qualified, and with comparable scientific productivity level. These systematic delays point to a dynamic asymmetry in career progression that we term as "pink queue": men advance to the top rank earlier, while women must wait longer, even when they have signaled comparable ambitions and scientific productivity levels. This delay is particularly noteworthy given the institutional environment, where ascending to higher ranks does not impose additional mandatory teaching or administrative burdens, that the literature recognizes as potential discouraging factors for female scholars.

Third, our analysis confirms the central role of scientific productivity in shaping academic careers. Higher h index quartiles systematically display higher probabilities of promotion and shorter waiting times. The Italian system does reward productivity, as expected under the design of the NSH and the broader meritocratic aspirations of the academic evaluation framework. However, even after conditioning on scientific productivity, gender differences persist. Within each quartile, women exhibit systematically lower probabilities and longer waiting times compared to men.

Moreover, a striking pattern emerges: female scholars in a given productivity quartile often exhibit career outcomes comparable to those of male scholars in the quartile below. This suggests that women must produce more or higher-impact research to achieve the same career progression as their male counterparts. Such a pattern is consistent with the existence of a double standard in evaluation processes, whereby equivalent credentials are not valued equally across genders, recognized in the literature in several contexts (see for example Gërxhani et al. (2023) for evaluation of co-authorship at an early career stage and Boring (2017) for teaching evaluation).

Our results remain qualitatively unchanged when controlling for academic age, proxied by the year of first publication, and this additional control does not materially affect the estimated gender gaps. Restricting the sample to bibliometric sectors, where the *h* index is more reliable, leads to qualitatively identical conclusions. These two additional robustness checks reinforce the credibility of our findings and suggest that unobserved differences in seniority or disciplinary measurement error cannot account for the observed gaps.

The use of multi-state models allows to investigate the phenomenon in its temporal dimension and uncovers aspects, such as the existence of asymmetries in the probabilities over time as well as in the time need to reach Full professorship, that remain concealed in more traditional frameworks. The findings are based on the case of Italian academia, yet offer insights that are transferable to comparable institutional contexts.

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