Gender Gap in the Labor Market: an Agent-Based Perspective

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1 Summary

We propose a novel approach to analysing the gender gap in the labor market, through the use of agent-based modelling.
First, we show how factors emerging from the literature contribute to creating and perpetrating the gap in our model. Then, we simulate different policy interventions.
Solutions such as imposing gender quotas or hosting motivational events to foster mentorship do not yield satisfactory results when introduced to our model.
Our simulations point, instead, towards a combination of policies aimed at increasing confidence for young women joining the work-force and enabling them with further opportunities for on-the-job training, for instance through the guarantee of increased family support.

2 Introduction

> "Gender equality matters for development. It's not only the right thing to do, it's also the smart thing to do, because gender equality is smart economics."
>
> — Caroline Anstey, Managing Director, World Bank.[1]

Even though decades have passed since the beginning of the feminist movement, and many milestones have been reached in the fight for gender equality, it is undeniable that a gender gap still exist in the labour market, in terms of wages and participation.
On average, in 2018, women in the EU earned 14.8% less per hour than men (Eurostat 2018). Women are excluded from the decision-making process: only 29% of the board members in the largest publicly listed companies registered in the EU are women, and they account for under 8% of CEOs (EIGE 2020). They are also heavily underrepresented in the high-paying STEM fields: women are significantly less likely to work in STEM jobs after a STEM degree (Beede et al. 2011), favouring education or healthcare instead. For instance, in the U.S. they make up for about half of the science PhDs, but for only 20% of the full professors (Shen 2013).
These evidences suggest that women's talents and skills are not being fully appreciated and put into use yet, with potential detrimental effects on society and the economy at large. In fact, more and more studies argue that gender equality can benefit the economy, by increasing overall wealth. The challenge of sparking the economic growth of a country is to a considerable extent linked to the role played by women in the society (Klasen et al. 2009, Aguirre et al. 2012). This insight is particularly valuable for countries with a low female labor participation rate, which could therefore enjoy larger marginal benefits from increasing it. Italy, for instance, has the second lowest rate of women labour participation in Europe, at 41% (International Labour Organization 2019).
Determining the cause of this gap is a complex question, that has interested researchers of multiple disciplines. Despite some controversial results, which are still an object of debate in the research community, one can identify numerous conclusions that are supported by a wide set of studies, and that help shed some light on the peculiarities of a woman's experience in the workplace. For instance, we analyse below how women face more difficulties in networking and being mentored in male-dominated environments (Ragins et al. 1990). We also see that women, despite being as

[1] Anstey 2012.

competent as men, show a tendency to under-perform in competitive environments (Niederle et al. 2010) or to actively avoid industries with a high degree of competition (Reuben et al. 2015).
In this paper we develop a model of the job market, reproducing the obstacles that women face in the workplace. Our goal is to visualise how these different factors contribute to creating the gender gap, and evaluate various targeted interventions to tackle this issue.

3 Background

Research on the determinants of the observed gender gap in the labour market spans across disciplines. Remarkably, similar conclusions have emerged from different observational contexts and research approaches.
Before we begin our overview of the literature, we must clarify that it is out of our scope to investigate whether the observed gender differences are due to nature or nurture. The presence of innate psychological differences between the sexes is still an issue on which scientists disagree on. Unfortunately, since it is also a culturally controversial topic, some of the research on this has not been of the greatest quality. A critical overview of the relevant work in the field suggests, however, that overall human variation is so high that, whenever sex differences are found in small samples, they become trivial or disappear as more data is gathered (Saini 2017).
A first strand of the literature attributes part of the gap to the role of same-gender mentors. Various randomised studies indicate that female mentors and professors have a strong impact on the subsequent performance and career decisions of women, while mentor gender does not appear to be relevant for men. A study carried out in the US Military Academy found that same-gender (and same-race) mentors greatly influenced the choice of branch for cadets belonging to underrepresented minorities (in this case, women and black people) (Kofoed et al. 2015). This suggests that proposing more diverse mentors may help increase diversity in sectors where strong disparities exist. Similar results have emerged in an academic setting, where having a female professor for Maths and Physics courses reduced the gap in performance by around two-thirds overall (completely eliminating it among high-performing students) and significantly increased the likelihood of female students choosing a STEM major (Carrell et al. 2010).
In a firm setting, mentor relations have been identified as key for career development, especially when the mentor is perceived in a friend role: it has emerged that, while the gender of the mentor does not seem to change the way the relationship is perceived, cross-gender mentorships tend to result in friendships which are limited to the workplace, where there is less potential for gossip about sexual involvement. Women are more damaged by this, as they are more likely to be in cross-gender mentor relations (Ragins et al. 1990).
Other scholars attribute part of the gap to behavioural differences in the workplace and in higher-education. Clear assumptions on the direction of the causality are difficult to make, but these factors still seem to contribute to the perpetration of the disparity. An example is competitiveness: in a study on high-performing MBA graduates, it was estimated that gender differences in taste for competition explained up to 10% of the overall wage gap (Reuben et al. 2015). Competitiveness was, in fact, a good predictor of future industry, with the most competitive individuals ending up in high-paying fields. It was also found that the effects of taste in competition mostly emerge over time through interaction with firms, when internships are converted into jobs or promotions take place, and are thus critical for career advancement.

Since wages are known to be affected by investments undertaken by agents based on their beliefs on future prospects, expectations are likely to play a role in explaining the gap. Filippin (2003) showed how expectations of discrimination can be self-confirming in a game-theoretical framework: they may lead to lower investment in on-the-job training and lower attachment to the workplace, which affects promotion decisions even when employers are unbiased. In a subsequent study on Bocconi graduates, it emerged that the expected gender gap accurately reflected the realised gap (Filippin and Ichino 2005). However, higher performing women seemed to significantly underestimate it.

Breen et al. (2002) proposed a Bayesian model to explain observed cross-country differences in gender segregation for jobs, and showed that agents with imperfect information on their probability of success in various occupations are strongly influenced by the preferences of past generations. Even when current-generation women and men are assumed to start out with the same beliefs, the process results in different career choices.

Manning et al. (2008) attribute about half of the gender gap in wage growth during early-career to differences in human capital accumulation. These are generated by lower levels of investment in on-the-job training and lower accumulated work experience for women, as they are more likely to work part-time. Behind these choices, anticipation of future intermittence of job-market participation, due to motherhood, definitely plays a role. Their results rule out the relevance of psychological differences and instead suggest that the rest of the gap can be attributed to *statistical discrimination*: the greater likelihood of a woman quitting her job when she has children induces employers to invest less in women and promote them less often (Lazear et al. 1990). Literature confirms that family considerations weigh significantly more on the career choices of women, on average, and this clearly emerges even before their entry on the job market (Goulden et al. 2009; RSC 2008).

Further evidence of the presence of implicit bias among employers comes from several studies in the STEM field (Shen 2013). For instance, in an experiment carried out in U.S. universities, faculty were asked to rate the profiles of students applying for a lab manager position based on CVs with randomly assigned genders (Moss-Racusin et al. 2012). Female students were judged to be less competent, offered less mentoring and a lower salary than identical male students. Most notably, women and men in the faculty were found just as likely to favour male students. The same study showed that this was not driven by hostility towards women, but instead by an unconscious bias determined by stereotypes on the lower competence of women.

4 Model

Our analysis has been carried out using agent-based modelling, which allows us to visualise how the actions and interactions of heterogeneous agents can influence aggregate behaviours and outcomes over time, and the impact of changes in their features or decision rules.

The history of agent-based models of the labour market is long but sparse (Neugart et al. 2018), and aimed at reproducing stylised facts (e.g. Okun's Law) or simulating policy interventions. The main advantage of ABMs over analytical models of job-search lies in the possibility to relax many of the standard assumptions simultaneously and account for a large number of factors, without the risk of mathematical intractability. Moreover, they allow to portray the agents' decision processes in a more natural way, taking the presence of partial information, learning and bounded rationality into consideration, instead of relying on the rational expectations paradigm. A recent example is that of WorkSim (Goudet et al. 2017), a large-scale calibrated model of the French labor market,

ultimately used as a tool to simulate the effect of changes in labor law.
As far as we know, no model in the job-search literature has ever focused on the gender gap nor has considered gender as a relevant variable for analysis[2]. Our model is thus fully original, and it was developed from scratch by relying on the gender gap literature. We have still been influenced, at different stages, by the aforementioned WorkSim, and by two agent-based models of the marriage market (Billari et al. 2007; Todd et al. 2005) which we have found illuminating for their simplicity and insightfulness.
We aimed to balance model complexity and the need for a credible depiction of the job market. We kept the functioning of the search process simple, and focused on the aspects that allowed us to account for gender differences as they emerged from the literature.
In the final version of our model, our agents interact in a toroidal squared-grid environment and have the following features:

– *Gender*: affects other features and job-search behaviour.
– *Age*: needed to model career development from entry in the market to retirement.
– *Skills*: talents or innate job-market valuable skills, as they emerge when the agent is interviewed for a job.
– *Education*: the level of education. It can be improved by on-the-job *training*, which all younger agents (under 35) undergo periodically. We allow for gender differences in the frequency (as observed in Manning et al. 2008), by having women train less often than men.
– *Aspiration level*: the self-perceived value of the agent (Billari et al. 2007), the magnitude of their career ambitions, used to determine whether a wage offer is acceptable. In our model, however, aspirations are not private information, although they do not enter in the recruitment process. It is a function of education, work experience, employment level and months spent unemployed. We include a perceived or expected gender gap, decreasing in employment level (Filippin 2003; Filippin and Ichino 2005), which reduces women's aspirations all else equal. This gap is also meant to incorporate behavioural differences in terms of lower competitiveness and concerns about family, which have a negative impact on women's ambitions (Goulden et al. 2009; Reuben et al. 2015; RSC 2008). At each period, agents adjust their aspiration upwards based on their network (Todd et al. 2005), defined in terms of Moore neighborhood, with women only being influenced by other women as suggested by the literature (Carrell et al. 2010; Kofoed et al. 2015; Ragins et al. 1990) .
– *Level*: we modeled different occupation levels, with 0 representing unemployment and 3 the executive role. We used Italian labour law classification for private sector employees as reference (excluding manual workers), i.e. *impiegati (1), quadri (2), dirigenti (3)*.
– *Level tenure*: the agent's work experience at the current level.
– *Total tenure*: the agent's work experience throughout her/his entire career
– *Trials*: only initialised for level 0 (unemployed) agents, it counts the years of unsuccessful applications until the agent finally becomes employed. Unemployed agents that cannot find a job for four years become inactive and leave the market for good.

[2]In Goudet et al. agents have genders, but this feature is only used to group them into households. Market behaviour is the same for both genders, and no further mention of the distinction is made.

- *Value*: the agent's job-market value as candidate for a position, perceived by the employer. It depends on objective characteristics (age, education, experience, level) and skills.

Job offers are introduced from above (as in Goudet et al. 2017[3]) and they are visible to all agents, as if they were posted on a LinkedIn-like platform. They come with required characteristics in terms of experience and education and are identified by their level and a wage. The compensation for each position depends on the level, the requirements and a ranking parameter which represents prestigiousness. Different rankings identify industries or firms that induce different levels of compensation: for instance a large consulting firm would have a higher ranking and thus pay more, given level and requirements, than a small family-owned business. We do not model firms explicitly, making no distinction whether progressions occur within the same company.
Job-search takes place once a month: agents apply for a single position among those accessible to them in terms of requirements and that offer suitable compensation. They are only allowed to level up (i.e. we only model changes that make them go up the corporate ladder) and only one level at a time. Once agents have made their applications, each position is filled by the most qualified candidate based on value. When an agent gets the job, his/her characteristics are updated accordingly.
At each time-step, retirements also occur and new agents are added to keep the total number constant. All of the new agents are 23 years old and have no work experience, as if they were approaching the labor market for the first time after university. Characteristics are randomly assigned and the probability of either sex is 50%.
Lastly we assumed that, with a certain probability, women younger than 35 become inactive to account for those who leave their jobs when they have children. We do not model other instances of voluntary resignation nor any kind of dismissal, and we do not consider changes in the economy.
The model was implemented in Python, relying on the *mesa* package.

5 Data / Parametrization

Since our model is rather simple, and it has no pretense of being able to incorporate all relevant aspects of the labour market, we concluded that calibration would make little sense.
Moreover, as we do not consider different industries nor economy-led rules for job creation and destruction, we realised that the choice of data to use as reference could easily become arbitrary.
However, since we aimed to explore various policy interventions, it was fundamental that our model could portray reality in a credible way. We thus opted for an educated parametrization, using data for Italy as reference, and focusing on the private market for the tertiary sector, where hierarchical organisations are common and there is a fairly structured recruitment process. Even in this case, unfortunately, we had to make several simplifying assumptions, as not everything that we were interested in measuring was available or in a form which could be suitable for our model.
We initialised the model with age distributions, unemployment rates and proportions at the different employment levels based on 2019 data (ISTAT 2019a,b). In the latter case, since the classification of professional figures is much more complex, we calculated shares over the sum of the three levels that we encoded: *impiegati* (Level 1), *quadri* (Level 2), *dirigenti* (Level 3). Indeed, most of the other existing profiles (such as self-employed, entrepreneurs or manual workers) could not be suitably represented by this model of job-search in any case.

[3] here, however, firms were explicitly modeled and job-search followed standard search-theory

When trying to set a realistic value for the probability of women quitting their jobs when they have children, the only reference we could find for Italy was a 2017 estimate (La Stampa 2018). We calculated our probability as the ratio of the number of resignations from women which cited family as the main reason over all women employed at Level 1 for that year[4] (ISTAT 2017). All other parameters were set based on values that made reasonable sense and ensured that our model was stable and produced sensible outputs, before introducing any intervention.
While access to more data and computational resources would surely benefit this effort, we find it can still give meaningful insights and potentially be a good first step towards a more sophisticated large-scale model.

6 Results

We carried out our analysis in three steps.
First, we devised an environment without any differences between men and women: the objective was to understand how to generate a stable market over time (as we do not model changes in the economy) and provide a *gold standard* system to strive towards. Then, we included the gender differences as motivated and described in sections 3-4. The initial distributions over the levels in this case were different for the two sexes, based on the data from section 5. This implies that this model starts with a prevalence of men in the higher levels, comparable to that observed in the Italian private sector. This model was meant to produce a more realistic labour market, with men reaching higher levels on average. Finally, we analysed the effects of different policies applied to the model with gender differences, with the objective of getting as close as possible to the gold standard.
All of the models were initially populated with "dummy" agents without any previous job history. Initial populations were made up of 200 agents, initialised as male or female with equal probability. The small sample size and batch size were constrained by the need to carry out several simulations on a model which, although relatively stylised, is still quite computationally heavy. Our aim was to track the career progression of new agents that join the labour market for the first time. Hence, we let the models run for 1200 steps (100 years) and looked at the results after a burn-in of 400 steps (33 years ca.), at which point most of the dummy agents had retired.

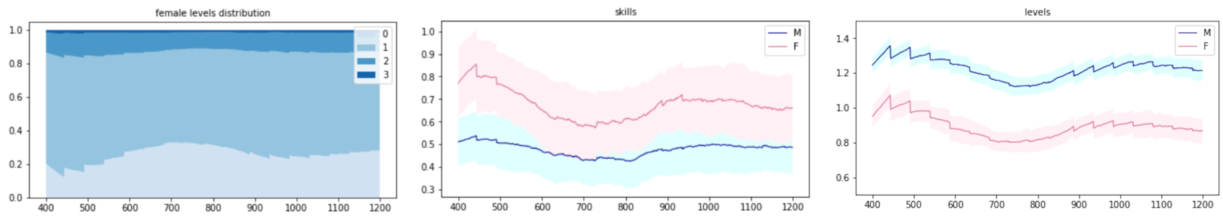
6.1 The gold standard

In this system there are no behavioural gender differences, male and female agents have exactly the same behaviour, hence, as one would expect, it yielded no statistically significant differences in outcomes for men and women. Both genders had statistically equal representations, average skills and average employment levels. Moreover, we could see that the average job-market value of the agents in the model was the same for men and women.

6.2 Introducing gender differences

By including gender differences in the model, female agents struggled to reach higher levels: we recorded far fewer women at Level 3 compared to men (Fig. 1a).

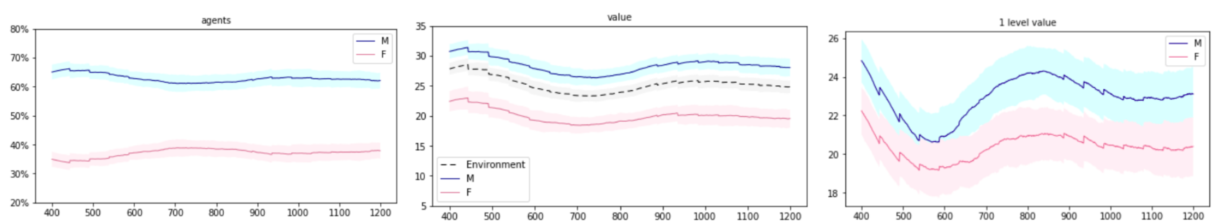
[4]The source reported that over 99% of all women resigning voluntarily in that year, including for reasons not related to motherhood, came from *impiegate* (Level 1) or manual workers.



(a) Levels distribution (female agents) (b) Average skills by gender (c) Average levels by gender

Figure 1: System with gender differences

The share of women in the system dropped to around 36% (Fig. 2a), but the remaining women had on average higher skills than men (significant at $\alpha = 0.01$, Fig. 1b): since we distributed skills equally across genders, this could mean that there are women that have the necessary talent to compete, but are not able to capitalize on it and end up leaving the job market, resulting in a loss of human capital.
With regards to the job-market value, compared to the previous model the male agents showed similar outputs, while women's average value was generally lower (Fig. 2b). This was driven by the joint effect of lower education (given different frequency of training) and lower average level (Fig 1c), which offsets higher skills. As a results the overall average value ended up being lower due to this disparity. By looking at the mean value for each level, it is interesting to notice that there were significant differences only in the first level (Fig. 2c). This suggests that it is at the beginning of their career, that women struggle to exploit their potential the most.



(a) Gender shares (b) Average values (c) Average values at Level 1

Figure 2: System with gender differences

6.3 Policy interventions

At this point, we introduced different policies aimed at narrowing the gap. To evaluate the results obtained, we compared them with the baseline model with gender differences and the gold standard, which was our target.
The first three policies we simulated consistend in an explicit preference for women in the recruiting process, motivational events with the goal of increasing their aspirations and initiatives for further training aimed towards young women who just got their first job.

6.3.1 Gender quotas

At each time-step, we required that a position may only be filled by a female agent, with a 33% chance. The effect of explicitly favoring women in the hiring process was positive with regards to

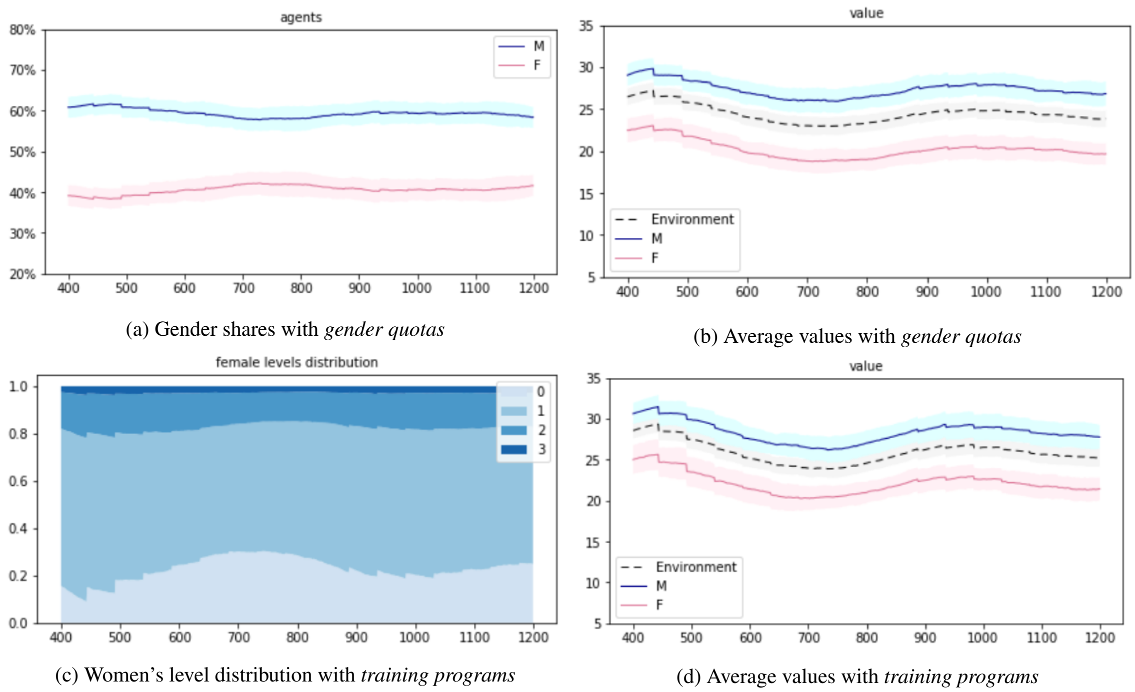
gender shares in the market with a stable female presence of 41%, compared to the 36% average of the baseline (Fig. 3a). Moreover, women were now reaching higher levels more frequently.
On the other hand, by looking at the average value of the system (Fig. 3b), we could see that it was lower than in the previous models (-10% with respect to the gold standard and -4% with respect to baseline). It is also relevant to note how *gender quotas* negatively affected the average level for men, while they did not affect that of women in a significant way.

6.3.2 Motivational events

During these events, younger female agents (under 35) interact with women with the highest aspirations in the model, as if proposing highly ambitious women as mentors, and update their own aspiration accordingly, instead of just relying on their neighbours.
We got positive effects on the aspirations of female agents by having an event every two or three months, which we understand may pose issues in terms of applicability. We thus opted for one event every six months, but this did not affect aspirations enough to offset the perceived gap. In real life, however, motivational events are a way to network, connect with companies and introduce oneself, but most of all they are an opportunity for the companies to have an extra recruiting session, by collecting CVs. This second aspect, which may be crucial, is not captured in our analysis, since we did not model firms explicitly, but it should definitely be included in further research.

6.3.3 Training programs

The goal of this policy was to reduce gender differences in investment on on-the-job training, by actively encouraging younger women to participate in the existing programs or providing them with dedicated opportunities. As we had seen in previous models, women mainly struggled compared to men when going beyond Level 1, which seemed to be a bottleneck in their careers. Therefore, we increased the training frequency for women at this level by 50%.
Due to the positive effect on education, the impact of this policy was positive in terms of level distribution (Fig. 3c), overall job-market values (+2% compared to the environment with heterogeneity, Fig. 3d) and gender shares (average 38% female presence). However, lower investment in training for young women cannot be solely explained by lower competitiveness or ambitions. We needed to also consider the fact that women on average spend more time on house-work and with children (Razavi 2012), hence, even when offered this opportunity, in reality a share of them may still prefer to decline. In addition to this, employers may be less willing to invest in training for women because they expect a greater risk of not returning the investment, if the women in questions decide to leave their jobs for this reason (Filippin 2003; Lazear et al. 1990)



(a) Gender shares with *gender quotas*

(b) Average values with *gender quotas*

(c) Women's level distribution with *training programs*

(d) Average values with *training programs*

Figure 3: Effects of different policy interventions

6.3.4 Combined Policy

Our last proposal was not focused on flattening the conditions between genders in an artificial way, but on creating *ad-hoc* solutions. At this point, we had identified younger women as the bottleneck, ruled out gender quotas, and shown that acting on motivation would only be beneficial if carried out at a high intensity, while encouraging participation in training programs seemed to be more promising as long as uptake was realistic.

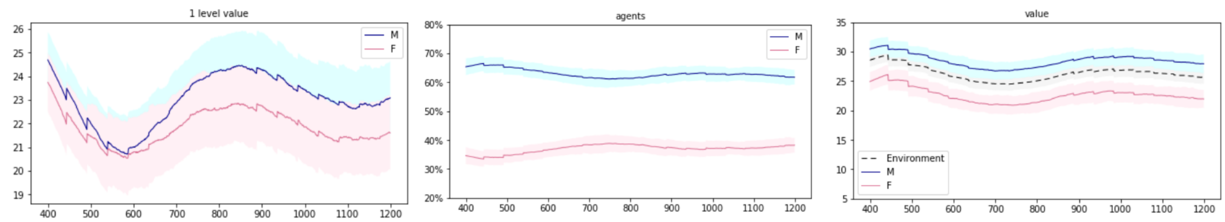
We interpreted our final policy as an increase in **family support**. Real-life implementations could include, among others, flexible timetables, babysitting bonuses and after-school programs. This kind of policy could be partially driven by firms but also directly supported and promoted by governments.

Since our model is very stylised, we simulated the *combined effect* of this intervention in the following way:

(i) *Ambitions*: the direct effect of the policy was modelled as a boost in women's aspirations, which increases as they get closer to maternity age. This is because motherhood is less perceived to be an obstacle to career anymore. Explicit support from the companies may also increase trust in firms and, thus, ambitions for career progression.

(ii) *Training*: the indirect effect of this policy is that it allows to allocate more time to training and personal development. This effect could also be amplified by explicitly encouraging on-the-job training and/or introducing dedicated programs. We still kept training frequency lower than for men, to account for possible underlying reasons unrelated to maternity.

This last intervention yielded an improvement in job-market values and aspirations for women, with no more significant gender gap in values at Level 1 ($\alpha = 0.01$, Fig. 4a). Compared to baseline, the share of women in the environment was higher (Fig. 4b) and the average value gap was decreasing (-32.7%, Fig. 4c). We still had a higher prevalence of women at Level 1, compared to men, but their average level was now higher compared to the previous simulations.



(a) Average values at Level 1

(b) Gender shares

(c) Average values

Figure 4: Effects of a combined policy

7 Conclusions

Given the outcome of our analysis, we conclude that a combination of policies would be the optimal approach to address the issue, if the assumptions on which our model is built are sufficiently close to reality. In particular, encouraging young women by making them feel more secure and boosting their ambitions, while facilitating them to take up further training turns out to be the best solution according to our simulations. This could be pursued for instance by increasing family support or by simply inducing companies, through economic incentives or prescritive regulation, to make sure they are investing equally in the training and fostering of women and men.

We find that explicitly favouring women when hiring helps with gender representation, but it may also be socially undesirable as it reduced the average value of active workers in our simulated environment.

Our model represent a novel methodological contribution to the gender gap literature, and it is intended as a first step in this direction. Numerous additions could be made to address its limitations, given more computation power and data.

For instance, modelling firms explicitly would allow us to analyse how more or less male-dominated sectors are affected by the same policies, portray networks more realistically and account for statistical bias (which would depend on the current state of the environment).

A more comprehensive model may also help to better assess how the gap affects the market in terms of productivity of the active work-force and waste of human capital. It might ultimately be possible to compare different policies in terms of social utility and carry out more informed cost-benefit analyses of each.

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