# An Agent-Based Simulation of Corporate Gender Biases

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**Abstract.** Diversity & Inclusion (D&I) is a topic of increasing relevance across virtually all sectors of our society, with the potential for significant impact on corporations and more broadly on our economy and our society. In spite of the value of human capital, Human Resources in general and D&I in particular are dominated by qualitative approaches. We introduce an agent-based simulation that can quantify the impact of D&I on corporate performance. We show that the simulation provides a compelling explanation of the impact of hiring and promotion biases on corporate gender balance, and it replicates the patterns of gender imbalance found in various industry sectors. These results suggest that agent-based simulations are a promising approach to managing the complexity of D&I in corporate settings.

**Keywords:** Diversity & inclusion · Agent-based simulation · Workforce analytics

## 1 Introduction

In spite of the growing body of evidence showing that companies with greater gender representation in leadership roles tend to outperform companies with fewer women [1–3], many industries continue to exhibit a sharp gender imbalance at senior and executive levels. These imbalances contribute to some of the severe problems we see across a variety of industries, ranging from gender pay gaps [4, 5] and high churn rates [6, 7] to discrimination lawsuits [8, 9]. In turn, these problems lead to high costs and internal instabilities, and expose companies to significant reputational risk. Beyond the private sector, gender imbalances also impact academia and the public sector [10, 11].

Given the extensive studies showing that greater gender inclusion can lead to corporate, economic and societal benefits, given the tangible negative implications of gender imbalances, and given the ongoing efforts ranging from individual activism to legislation, why are there still such significant gender imbalances?

We believe that the relative lack of progress is due primarily to the sheer complexity of the problem, and the lack of tools that can deal with this degree of complexity. Today, Human Resource management is considered a "soft" skill; workforce analytics platforms rely on measurements and statistical analysis, but are unable to


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capture the myriad events, interactions, attitudes and subjective preferences of employees.

Further, each organization is a unique "ecosystem", and what works for one organization is unlikely to work the same way for another. When you also consider that the impact of personnel initiatives can take months or years to be observed, and that missteps can be extremely costly, it's no wonder that leaders are reluctant to take decisive action.

In this paper we use an agent-based simulation, one of the primary tools of *Complexity Science*, to study a particular aspect of corporate gender imbalance: by simulating the career advancement of employees at typical companies, we can analyze the impact of introducing gender bias in the promotion process.

Under reasonable assumptions, we find that gender biases in promotion can yield the kinds of gender imbalances that are typical of many companies, with decreased representation of women at higher corporate ranks. We also find that by adjusting gender biases in hiring as well as promotions, it is possible to develop gender imbalances that match the patterns observed in different industries.

Our findings, in line with other studies, show that agent-based simulations are a powerful tool for workforce analytics. More importantly because the simulations capture detailed aspects of individual behaviors and interactions, our approach holds great promise for theoretical and applied research into Diversity & Inclusion (D&I) – a topic of great current interest with significant economic and societal implications.

After introducing some background materials, the remainder of this paper describes the simulation we have developed, and then presents some of the results we obtained with the simulation, including matching to published data about gender imbalances across multiple industries. The paper is brought to a close with some conclusions and suggestions for future opportunities to expand this line of work.

## 2 Background

### 2.1 Gender Biases in the Workplace

Although female labor force participation is increasing, women still are severely underrepresented at the top level of organizations. According to the U.S. Department of Labor, women account for almost half of the total labor force in the U.S., and more than 40 percent of those have college degrees; however, in 2018, women only held 5% of chief executive officer positions in S&P 500 companies, 21.2% of board seats and 26.5% of the executive and senior-level management positions [12].

Bielby and Baron [13] categorized the causes of the gender gap in upper management positions into *supply-side* and *demand-side* explanations. According to supply-side explanations, the divergence in employment outcomes between women and men are mainly due to differences in gender-specific preferences and productivity [14], therefore individual attributes determine the gender inequalities in the workplace [15]. For example, some believe that balancing family life and work lowers women's promotion rate as women need to take on a larger share of domestic and parental responsibilities [16]; others hypothesize that women, in general, are less competitive than men so they may be reluctant to compete for promotion [17].

In contrast, demand-side explanations suggest that gender stratification in the workplace is primarily due to gender-specific barriers; demand-side explanations focus on the institutional constraints and managerial biases faced by women in climbing the career ladder. For example, a male-dominated board of directors may prefer to hire male executives [14]; women must meet higher performance standards for promotion than their male colleagues [18, 19]; stereotypes of leadership style differences favor men in advancing to leadership roles [20].

In this paper we present a simulation that provides indirect but compelling evidence for a demand-side explanation. Specifically, we simulate the typical career advancement of employees in an organization without incorporating gender-specific preferences and characteristics, such as education level and career interruption. Rather, we focus on demand-side barriers, specifically focusing on the impact of introducing gender biases in the promotion process, which we believe is a significant institutional barrier that prevents women from attaining senior roles. We find that under some very simple assumptions about the presence of gender biases in promotion, it is possible to replicate the types of gender disparities that are observed in typical companies across a variety of industries. Hence, while we cannot conclusively prove that gender imbalances are due to gender-specific barriers, we demonstrate that the existence of gender-specific barriers would yield the kinds of imbalances that are observed empirically.

Another gender-specific barrier that we examined is bias in hiring. As suggested in a recent report by McKinsey & Company and the nonprofit organization *Lean In* [21], women may remain underrepresented at manager levels and above because they are less likely to be hired into entry-level jobs, in addition to being less likely to be hired or promoted into manager-level positions.

We extended our simulation to capture a simple form of hiring bias, and found that by adjusting the hiring and promotion biases simultaneously we are able to replicate industry-specific gender balance patterns as reported in the McKinsey study.

Before introducing our simulation, we provide some additional background information on agent-based simulation and its application to corporate D&I.

## 2.2 Agent-Based Simulation

The issue of diversity in companies – from early-stage startups to global corporations – is a highly complex problem, with interconnections and ripple effects that range from individuals to entire corporations and even society as a whole.

Our work is rooted in the theory and application of *Complexity Science*, a discipline that first took shape in the late 1960s with the seminal work of Thomas Schelling on the emergence of segregation [22], and became a full-fledged area of academic inquiry in 1984 with the creation of the Santa Fe Institute.

Complexity Science is a broad field that encompasses a variety of technologies for studying complex systems, *i.e.*, systems whose behavior depends in complex and often unpredictable ways on the behaviors of many individuals who interact with one another and with their environment [23]. One of the primary tools for the analysis of complex systems is *agent-based simulation*, a methodology that combines behavioral science and computer modeling [24]. Agent-based simulations capture the behaviors of individuals, and their interactions with other individuals and with their environment, to simulate the way in which the overall behavior of a system emerges through these complex chains of interactions.

Our team has previously developed dozens of agent-based simulations to solve complex problems across many sectors and many types of organizations, including corporations, government agencies and foundations. The majority of these applications involved simulating and analyzing the behavior of human systems, including consumer marketplaces [25, 26], energy consumption in commercial buildings [27], manpower and personnel management for the U.S. Navy [28], healthcare [29] and computer security [30]. In this paper we focus specifically on the application of agent-based simulations to corporate D&I.

### 2.3 Simulating Corporate D&I

A majority of the research on gender inequality in the workplace is conducted by applying statistical methodology on collected data. These statistical approaches have significant limitations, including the fact that they hide any dynamic information as well as details about individuals.

In contrast, agent-based simulations are ideally suited to analyze and predict the performance of human organizations by capturing the mutual relationships between individual employees and their organization: the performance of an employee influences the success of an organization and, conversely, the environment created by the organization influences the success of the individual employee. This sort of "feedback loop" is part of what makes workforce management so complex, and it is exactly the type of problem that lends itself to analysis using agent-based simulation.

In this light, agent-based simulation promises to be a valuable tool to capture the impact of D&I on corporate environments: to the extent that a company influences people's experiences differently based on personal traits, the company's performance will in turn be impacted. In fact, the connection between D&I and complexity has been proposed by others [31]. More specifically, agent-based simulation has already been used to analyze issues related to corporate D&I. For example, the simulation built by Bullinaria [32] shows how ability differences and gender-based discriminations can lead to gender inequality at different hierarchical levels within an organization; Takács *et al*. [33] found that discrimination can emerge due to asymmetric information between employer and job applicants even without hiring biases; Robison-Cox *et al.* [34] used agent-based simulation to test the possible explanations of gender inequality at the top level of corporations, and found that giving men favorable performance evaluations significantly contributes to the gender stratification of top-level management.

Our agent-based simulation takes a step further and simulates ongoing activities and transitions, to show the dynamics of gender imbalance at each level of the hierarchy that result from imposing promotion biases or hiring biases. The simulation replicates the week-by-week operations of a typical company with men and women distributed across four levels: entry-level employees, managers, vice presidents and executives. In a pilot project, we were able to simulate the impact of gender biases in the promotion process, which leads to the kinds of gender imbalances seen in real companies, with increasing representation of men in higher levels of the company [35]. We also reported some preliminary results showing that removing biases in a company that is already imbalanced is not a very effective strategy, as gender inequalities can persist for significant periods of time. Our findings are in line with those of Kalev *et al.* [36], who found that programs targeting lower levels of management, such as diversity training and performance evaluations do not help to increase diversity at higher corporate levels, and that imbalances persist after organizations adopt these diversity management programs.

In this paper, we focus on the establishment of gender imbalances as a result of promotion biases and hiring biases, comparing our results to recent reports.

## 3 The Simulation

One of the most powerful aspects of agent-based simulation is that it captures the way real-world systems work in an intuitive, human-centric fashion. This means that anyone who has familiarity with the problem can contribute to the design of the simulation. In a sense, agent-based simulation democratizes analytics, because it does not require knowledge of advanced mathematical or computational techniques. Compared to more traditional approaches to analytics – in which a data scientist analyzes large amounts of data using analytical tools to look for patterns, and the domain expert is relegated to making sense of the identified patterns – agent-based simulation allows the domain experts to be more closely involved both with the model design and with the analysis of the results [25].

The simulation we developed for this paper is a good example, as it is based on simple assumptions about the operations of a typical company. One of us has significant experience developing simulations of organizations, but the simulation we now introduce should be intuitive to virtually anyone who has even a basic understanding of the functioning of companies.

### 3.1 Core Elements of the Simulated Company

In our simulated company, there are two types of employees, which we associate with men and women. Notice that because we are only interested in studying the impact of institutional barriers, our simulation assumes that men and women have identical abilities and that their performance is also identical. Similarly, gender-specific preferences and characteristics like education level and career interruption are not incorporated in the simulation. All of these details could easily be added if one were interested in studying related phenomena. However, for the present study we wanted to focus exclusively on the impact of biases in promotions and hiring.

Employees fall into one of four increasing levels: entry level, managers, VPs and executives. The company starts with a user-defined number of employees, distributed across levels in a way that matches a typical company, with smaller numbers of employees in higher levels.

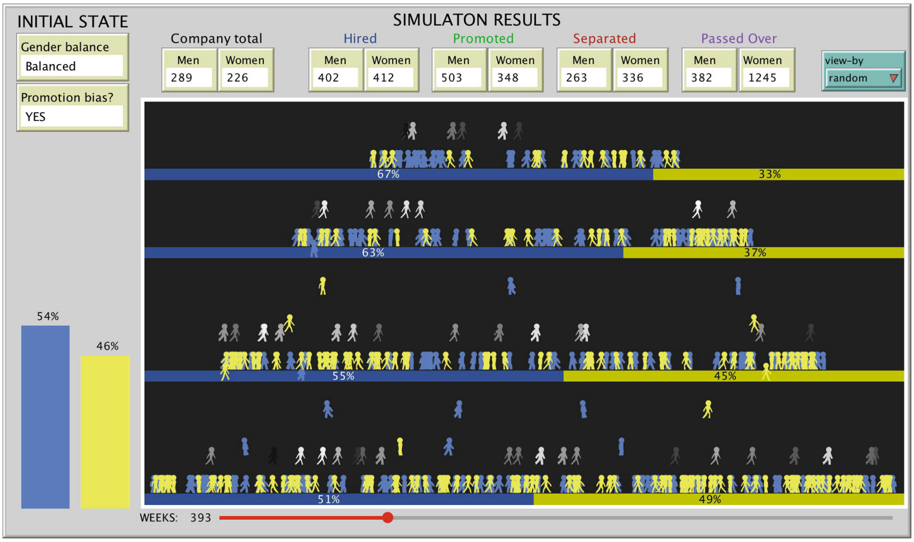



**Fig. 1.** Screenshot of the simulation, showing four levels of employees. Employees that appear between levels are in the process of being promoted, while employees that hover just above a level are in the process of separating. Men are shown in blue (dark), women in yellow (light).

The company is assumed to grow over time, creating vacancies at each level. In addition, employees may separate from the company, creating additional vacancies. Vacancies at the entry level are filled through hiring from a hypothetical external pool of candidates, while vacancies at all other levels are filled by promoting individuals from the level immediately below, which, in turn, create additional vacancies at the level from which someone was promoted.

For this version of the simulation we do not simulate direct hiring into higher levels, nor do we allow promotions to skip levels. However, these and other details could be added if we were interested in exploring the effects of such modifications.

Figure 1 is a screenshot of the simulation, which was developed with the NetLogo simulation platform [37]. Each "floor" acts as a simple histogram, showing the percentage of men and women at that level. The two vertical bars on the left show the overall gender balance across the entire organization.

## 3.2 Simulating the Hiring Process

Vacancies at the entry level can occur as a result of overall company growth, or from entry-level employee separations, or from entry-level employees being promoted to the manager level.

When a vacancy occurs at the entry level, the simulation assumes that a new employee will be hired from a potentially infinite pool of candidates. By default, there is an equal chance of hiring a man or a woman. Gender biases in hiring are simulated by setting a *hiring-bias* parameter that changes the probability of men (or women) being hired.

When an employee is hired, the simulation begins to track the amount of time they have been with the company.

### 3.3 Simulating Promotions

When a vacancy appears at any level above the entry level, promotions are simulated by identifying a pool of "promotion candidates" from the level immediately below, and then choosing randomly one employee from that pool.

By default, the promotion pool is set as a percentage of the total number of employees at that level, and is based on the promotion score of each employee. Also by default, the promotion score of each employee is a normalized value based on the amount of time the employee has spent at the current level, relative to the amount of time spent at that level by the most senior employee at that level. In other words, in the absence of a bias, promotions are based strictly on seniority within each level.

Gender biases in the promotion process are simulated by adding a *promotion-bias* value to the promotion scores of men[1]. This bias is applied uniformly at all levels.

When an employee is promoted, its seniority at the new level is set to zero, while the simulation still tracks the total amount of time that the employee has been with the organization.

### 3.4 Simulating Separations

We simulate employee separations without regard as to whether the employee left the company voluntarily or by being terminated. We simulate separations at each level as a random event, whose frequency is proportional to the number of people at that level.

Employees are chosen for separation through a process similar to promotions: a pool of separation candidates is formed by selecting a percentage of employees at that level that have the lowest promotion scores. The actual employee to separate from the company is chosen randomly from that pool.

If the promotion-bias is set to a non-zero value, the same bias that influences promotions will also influence separations.

### 3.5 Tracking Individual and Aggregate Results

One advantage of agent-based simulations is that they can simultaneously provide aggregate, population-level metrics to match those commonly used for workforce analytics, while preserving all of the details about individuals. For example, we can track traditional metrics such as overall company size, gender balance and churn rates, but we can also track how many times any given individual was passed over for a promotion (*i.e.*, when someone less senior at the same level was promoted to the next higher level).

We use the aggregate metrics to ensure that the simulation is behaving "reasonably" by matching performance metrics to what is seen in real companies, and then we can

[1] The promotion-bias parameter can be positive or negative to simulate biases that favor men or women, respectively.

drill down to perform a much finer level of analysis, for instance studying the impact of promotion biases on the likelihood that any given individual will be passed over for promotion.

We now turn to a description of the experiments we ran to test the impact of promotion and hiring biases.

## 4 Simulation Setup and Results

### 4.1 Parameter Settings

For all results reported here, the company begins with a total of 300 employees, 150 women and 150 men. The employees are distributed across the four levels in a way that roughly simulates a typical company: 40% at the entry level, 30% at the manager level, 20% at the VP level and 10% at the executive level. Note that we have tested the simulation with other settings and found that as long as there are at least 100 or so employees at the start, the overall results are consistent.

During the simulation, each time tick is set to correspond to a seven-day period. At each time step, random numbers are drawn to determine whether separations, hires or promotions need to take place. The frequencies of each of these occurrences are set so that, over the course of a simulated year, the overall growth and churn rates are within a range that would be consistent with a "generic" company: the company grows by 10% each year, while we target an annual churn rate of 20%, which is in accordance with national average churn rates [38].

For promotions we set a candidate pool size of 15%: in other words, when someone needs to be promoted to a higher level, we select the 15% of employees with the highest scores, and then randomly choose one of them for promotion. For separations, we set the candidate pool size to 50%, meaning that someone is selected randomly from half of the employees at each level with the lowest promotion scores. We have tested different size candidate pools and found that the results do not change significantly[2].

The simulation includes several steps that invoke a random number generator. This results in variance across simulations[3]. Unless otherwise specified, each of the results shown below was obtained by averaging the results from five *Monte Carlo* simulations with each parameter setting. We found that results do not vary significantly as we increase the number of simulations.

### 4.2 Experiment 1: The Impact of Gender Biases in Promotion

In the first set of experiments we wanted to establish a baseline and then test the impact of systematically increasing the degree of gender bias in the promotion process. Figure 2 shows the gender balance at each level during a 30-year simulation when there is no promotion bias or hiring bias. The figure shows that, in the absence of

[2] Smaller pool sizes coupled with non-zero promotion biases tend to create cyclical behaviors which do not influence the overall results but create some unnatural dynamics.

[3] To ensure reproducibility, we have the ability to select the seed for the random number generator.

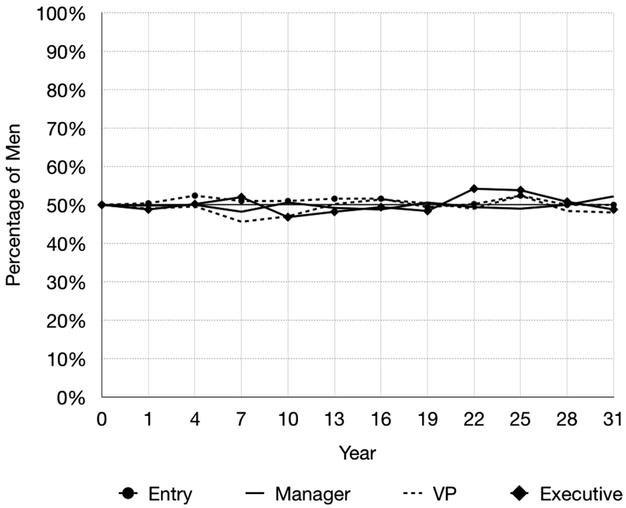



**Fig. 2.** Timeline showing the fluctuations in gender balance across all four levels during a 30-year simulation. For this figure the promotion and hiring biases are set to zero.

biases, the gender balance stays at 50–50 throughout the simulation, with only small fluctuations due to the inherent randomness of the simulations.

Next, we tested the impact of increasing the promotion bias to 0.1, 0.3 and 0.5. As mentioned earlier, in the absence of biases, each simulated employee's promotion score is simply its seniority relative to the most senior employee at that level. Hence all the promotion scores prior to the application of a gender bias are between 0 and 1.

Adding a promotion bias of 0.1 thus means that while women's scores will still be in the range [0, 1], men's promotion scores will be between 0.1 and 1.1. Similarly, at the highest level of bias reported here (0.5), men's promotion scores will be between 0.5 and 1.5, while women's promotion scores will stay in the range [0, 1]. In all three sets of simulations, the hiring bias is set to zero.

As can be seen in Fig. 3, a bias of 0.1 in promotions begins to show an interesting pattern: while the entry and manager levels continue to stay roughly at 50-50, the VP level (dashed line with no symbol) is starting to show an imbalance in favor of men, while men now make up roughly 60% of the executive level.

The pattern becomes much more evident in Fig. 4, which shows the gender balance at each level when the promotion bias is set to 0.3 (top) and 0.5 (bottom). Several interesting phenomena are worth pointing out.

First, we see that, even though the promotion bias is a single parameter that works uniformly at each level, the successive promotions compound the effect, so that the gender imbalance is greatest at the executive level: after several simulated years, the executive level reaches a make-up of approximately 80% men when the bias is at 0.3, and exceeds 90% men when the bias is at 0.5.

Second, increasing the bias has the effect of increasing the degree of imbalance, but also the speed with which the imbalance spreads through the organization: notice that with a bias of 0.3, the imbalance at the executive level builds gradually over a span of

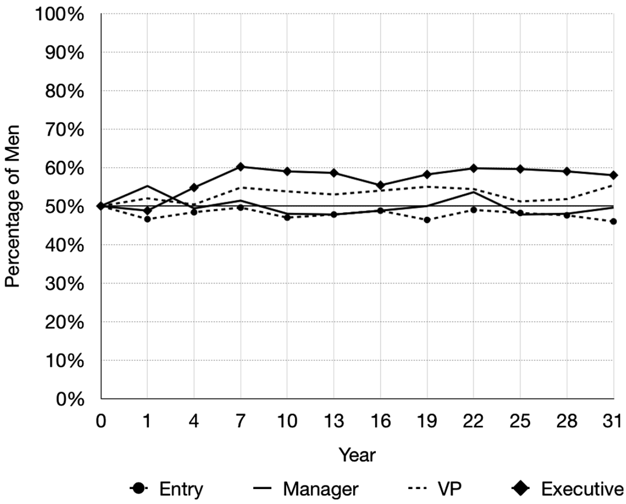



**Fig. 3.** Timeline showing the fluctuations in gender balance across all four levels during a 30-year simulation when the promotion bias is 0.1 and hiring bias is zero.

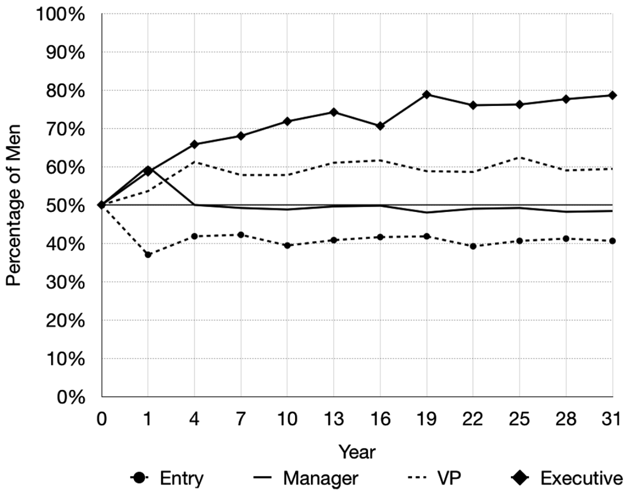
nearly 20 years; but when the bias is 0.5, the executive level crosses the 80%-male mark in less than five years, and has essentially leveled off by year 10.

Third, there is a surprising effect at the entry level: even though there is no hiring bias (we confirm in the simulation that the same number of men and women are hired), and even though women are being terminated more often than men (because the promotion score influences separations) we see that women make up an increasing percentage of the entry-level population, reaching roughly 60% when the bias is 0.3 and 70% when the bias is 0.5. The reason for this “reverse imbalance” is that men are being promoted at a much higher rate than women, so that women are being left behind. In reality, this is not uncommon in the real world: in many industries you find greater numbers of women in entry-level positions, and women often describe the negative experience of being “stuck” while their male colleagues get promoted.

This last observation illustrates another great aspect of agent-based simulations: unlike typical “black-box” models, with an agent-based simulation it is possible to dig into the detailed activities to understand the origin of observed macroscopic phenomena, *i.e.*, emergent behaviors. We will come back to this point in the closing section.

Overall, the results of these experiments show that, starting with a very simple assumption, we can capture some qualitative phenomena that match our observations of real-world companies: increasing gender imbalance at higher levels, and women being stuck in lower levels.

In the next section, we show how, modifying an additional parameter, we can start to customize the simulation to capture data observed from specific industries.



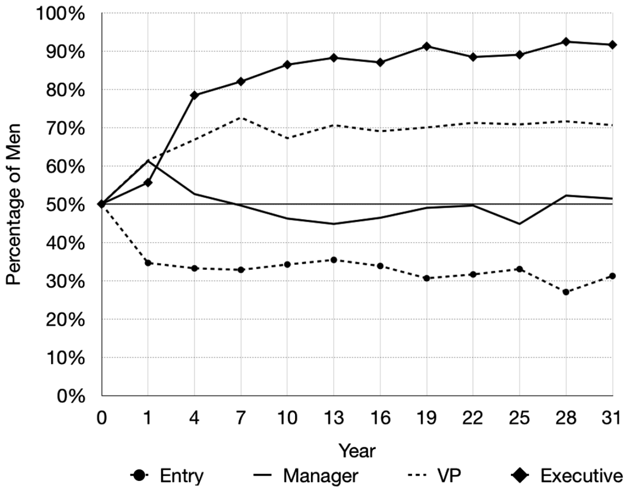




**Fig. 4.** Timeline showing the fluctuations in gender balance across all four levels during a 30-year simulation when the promotion bias is 0.3 (top) and 0.5 (bottom). See text.

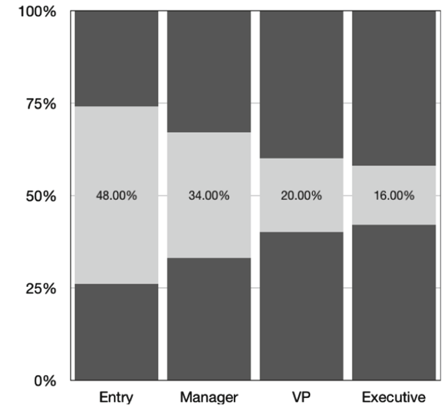
### 4.3 Experiment 2: Combining Promotion and Hiring Biases to Match Industry-Specific Imbalances

While the patterns shown in Figs. 2, 3 and 4 already look remarkably like those we observe in real companies, we wanted to see if, using a minimal set of assumptions, we could match real-world data on gender imbalances for more specific cases. To this end, we used our simulation to match data from McKinsey's and LeanIn's *Women in the Workplace* report [21].

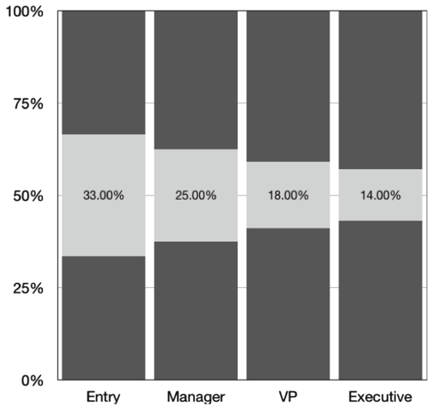
In the figures that follow we ran simulations for ten years, and measured the gender (im)balance at each level. In all simulations we modified two parameters from the baseline case: the promotion bias and the hiring bias. In general, as mentioned earlier, higher promotion biases create larger imbalances at higher levels, and can lead to reverse-imbalance at the entry level. In other words, if we think of the company's gender balance as a funnel, that funnel is somewhat shallow at low levels of promotion bias, and steeper at high levels of promotion bias.

In contrast, the hiring bias has an immediate impact only on the entry levels. Hence we expect that increasing the hiring bias will make the overall funnel narrower, while the promotion bias level will influence the steepness of the funnel.

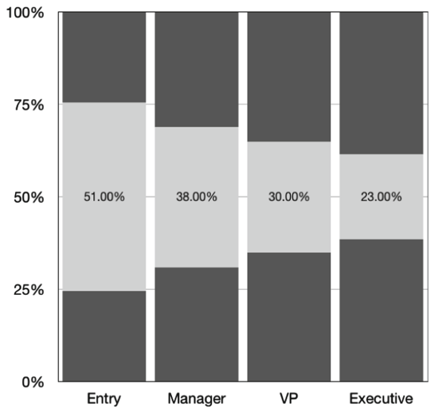
In Fig. 5, we show the ten-year gender balance data from our simulation using a format that is meant to mimic the format used in the McKinsey report, which show gender balance as a horizontal funnel, with entry level on the left, and executive level



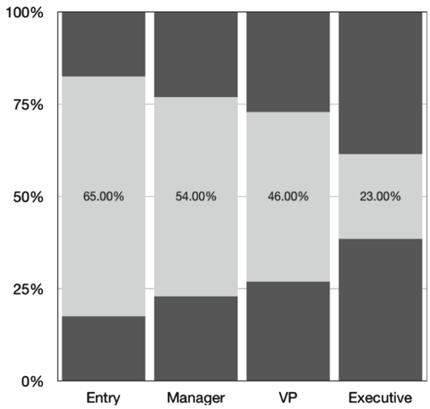

***(A) Transportations and Logistics: Promotion 0.5, Hiring 0.3***




***(B) Technology (Software & Hardware): Promotion 0.4, Hiring 0.5***




***(C) Financial and Professional Services: Promotion 0.3, Hiring 0.2***




***(D) Hospitality: Promotion 0.3, Hiring -0.1***

**Fig. 5.** Simulating the gender make-up of different industries by adjusting both promotion and hiring biases. See text.

on the right. The McKinsey report uses six levels (entry, manager, director, VP, SVP and C-Suite), so we selected the four levels that match the levels used in our simulation: entry, manager, VP and Executive (C-Suite).

Starting with Fig. 5(A), we see that setting the promotion bias to 0.5 and hiring bias to 0.3 results in a relatively steep funnel, with just under half women at the entry level, but only 16% women in the top ranks – a threefold reduction in representation. This shape matches closely the gender imbalances observed in the *Transportations and Logistics* sector in the McKinsey study.

In Fig. 5(B), the promotion bias is lowered to 0.4, but the hiring bias is raised to 0.5. As expected, the overall funnel becomes much narrower, with only 33% women at the entry level, and it is not as steep: while the top rank, at 14% women, is slightly lower than in Fig. 5(A), this means that the representation of women in the top ranks represent a 2.4x reduction relative to the entry level. This graph matches closely the gender data from the *Technology (Software and Hardware)* sector in the McKinsey study.

In Fig. 5(C), the promotion bias is further lowered to 0.3, and the hiring bias is only 0.2. The lower hiring bias results in women making up almost exactly half of the entry level, while the lower promotion bias leaves nearly 25% of women in the top ranks. These results match closely the gender data reported by McKinsey for the *Financial and Professional Services* sector.

Finally, Fig. 5(D) shows a pattern that resembles the gender imbalances observed in the *Hospitality* sector, which tends to be dominated by women at the entry level, but with only a modest female representation at the top ranks. We obtained this graph by keeping the promotion bias to 0.3, but setting the hiring bias to −0.1, *i.e.*, the hiring bias actually favors women.

## 4.4 Simulation Accuracy

To test the accuracy of our simulation, we calculated the root-mean-squared deviation (RMSD) between each simulation and the data provided from the McKinsey study, given by the formula:

$$RMSD_i = \sqrt{\frac{(L0_D - L0_S)^2 + (L1_D - L1_S)^2 + (L2_D - L2_S)^2 + (L3_D - L3_S)^2}{4}} \tag{1}$$

Where $RMSD_i$ is the RMSD for a given industry $i$, and each squared term captures the difference between the gender balance data (subscript $D$) and the simulation (subscript $S$) at a given level, and the division by 4 represents the fact that we are averaging the result across the four levels. In all cases shown in Fig. 5, the RMSD was below 6%.

## 5 Discussion

We have introduced an agent-based simulation that captures, in a simplified form, some of the gender imbalances that are observed across a variety of industries. What is perhaps most surprising about our findings is that we are able to capture several phenomena through some very simple assumptions, and by varying a small number of parameters.

Of course, the fact that our model is able to reproduce some of the observed phenomena does not mean that we are accurately capturing the true causes of these phenomena: it is possible that the mechanisms we hypothesized are not representative of real-world corporate functions, and that the similarity between our results and real-world observations are purely coincidental.

However, what we have been able to show is that by making some very simple assumptions about the functioning of a company, and introducing a minimalistic notion of bias, the company dynamics result in gender imbalances that are very similar to those observed in the real world. Because our model is capturing the causal links between the behaviors of individuals and the emergent behaviors of a company, and because our model is very parsimonious in its assumptions, we are confident that our model, while certainly simplistic, is capturing some fundamental aspects of corporate function that reflect real-world contexts.

It is worth noting that most of the research on gender inequality in the workplace is conducted by applying statistical methods to observed data. This more common approach has a number of limitations, including the fact that it is only capturing present conditions, it removes any information about dynamics, it hides details about individual interactions, and, most importantly, it tends to identify correlations that may or may not be due to causal relationships. But the most significant advantage of our agent-based approach relative to statistical simulations is that, because we are capturing causal links, the same tool that is used to match observed data can then be used to test the likely impact of different initiatives. In other words, we believe that the simulation we presented can be used to help corporations understand the likely outcomes of different D&I initiatives.

We see this project as the beginning of a systematic study of the impact of D&I on corporate performance. This highlights one more advantage of the agent-based approach: it is possible to add details to a model to increase its predictive power without having to throw away the previous model. For instance, we could explore the impact of the candidate pool not being infinite and perfectly balanced; in fact, a former student of ours developed an additional agent-based simulation that shows how job candidates may be influenced by the perceived level of inclusion and diversity of a company, and how this will impact the talent pool available to any company [39].

Even within the promotion model itself, there are many ways in which we could increase the fidelity of the model to explore the impact of different assumptions and of different initiatives. For example, we could add the ability to hire people directly into higher levels. We could add the notion of employee satisfaction, and tie it to individual experiences in a way that influences retention rates: in the current model, as bias increases, women tend to get passed over for promotion much more frequently than men, and end up being stuck for a long time; in the real world, these factors undoubtedly lead women to quit, resulting in lower retention rates for women – a phenomenon that is common across many male-dominated industries. We could also simulate the impact of having managers of a different gender on satisfaction and career advancement. In other words, this model can serve as the basis to explore a large number of hypotheses about the sources of gender disparities, and to test the likely impact of different interventions.

Finally, although in this paper we have focused on gender, it is possible to represent other personal characteristics that impact an employee's experience, such as ethnicity, race, religious beliefs, sexual orientation, physical and cognitive abilities, and so on. We have actually begun to develop some agent-based simulations that include other facets of diversity, and have already encountered some complex, fascinating issues that suggest entirely different ways of thinking about diversity and inclusion. In all, we are optimistic that our work and the work of other complexity scientists can lead to a dramatic shift in how people think about diversity and inclusion, and, more importantly, what corporate leaders can do about it.

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