Gender Bias Report

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1 Executive Summary

1.1 Theme and Motivation

We examined how hiring, promoting, and leaving patterns might produce or reinforce gender imbalances at different levels of a company's hierarchy. Our primary questions were about whether subtle biases in hiring and promotion probabilities could lead to fewer women in senior positions over time and how quickly such disparities emerge or stabilize.

1.2 Key Questions

This study explores the theme of gender bias in corporate settings, focusing on potential disparities in promotions and career outcomes. The specific questions addressed include:

1. **How do varying departure rates—some groups leaving more frequently than others—interact with hiring and promotion biases to shape long-term gender composition at each level?**
2. **If women and men begin in equal numbers at the bottom, but promotions go just a bit more often to men, does this slight bias gradually develop into a large under-representation of women at the top?**
3. **How does gender bias impact career progression over time in hierarchical organizations?**

1.3 Methods and Simulations

To answer these questions, we built a simulation-based model that captures the dynamics in the corporate hierarchy. This allowed us to investigate different scenarios by changing parameters such as:

- Hiring probabilities: The probability of hiring women compared to men for entry-level jobs.
- Promotion probabilities: The relative promotion probabilities for women and men as openings become available.
- Departure rates are when employees of each gender leave the organization at all hierarchical levels.

To stimulate the bias in the job force, men were slightly more likely to be promoted, and women had higher departure rates at every level. Running such simulations over dozens of years, we observed how slight biases could magnify and compound with time.

1.4 Key Findings

Minor biases have large impacts: We looked at how small differences in the likelihood of hiring or promoting women compared to men can lead, given time, to big differences in who ends up in senior roles. For example, imagine a situation where new hires are just more likely to be men—say 60% men and 40% women instead of a perfect 50–50 split. Although that initial difference seems small, when we simulated what happens over many years, we found that the top leadership positions had a much smaller fraction of women than men.

Promotion bias compounds inequalities: Another scenario began with equal numbers at the lowest level. However, at each promotion, we favor men by giving twice the probability of moving up whenever a position opens. In simulated time, this weak advantage grows over a long time into the dominance of the highest rank by men despite having begun with equal numbers of men and women.

Departure rates lock in disparities: If women were slightly more likely to leave the company at each level due to whatever reasons. For example, a 1% higher departure rate difference at each level or increasing departure rate from the lower level to the upper level. This, combined with biases in promotion, could lock in a pattern where very few women reached the top. On the other hand, if we adjusted the parameters to make the hiring process more balanced or the promotion process fairer, we could prevent or reduce these imbalances.

1.5 Impact and Future Directions

Our project highlights the potential inequalities between genders in the job force. In order to address these issues effectively, we need to consider the following:

- **Early intervention:** we need to address the inequalities at the lower level first and move further up to ensure both genders are being treated fairly and promoted fairly.
- **Understanding the leave rate:** we need to understand the possible reason why one gender has a potentially higher leave rate compared to the other one. What possible steps can we take to ensure a balanced leave rate to promote equality?
- **Regular evaluations:** we need to regularly check on our evaluation process for recruitment and promotion to make sure there are no innate biases.

1.6 Takeaway

In summary, our models showed that even a tiny difference in hiring chances or a higher promotion rate for one group could, given enough time, add up to large differences in who holds senior roles at a company. As a result, it is crucial that we spot these differences early and make changes.

1.7 Figures

These figures show an example of the compositions of genders in the company at different positions captured at four different times. It started off with even composition, but men started to dominate due to the tuning of different parameters.

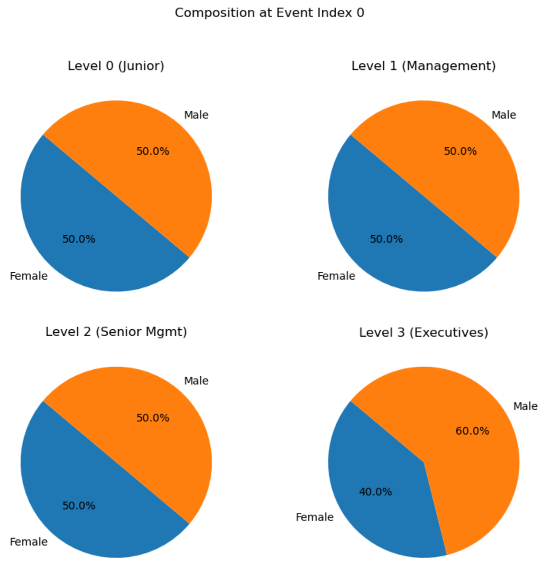

Figure 1: $t = 0$

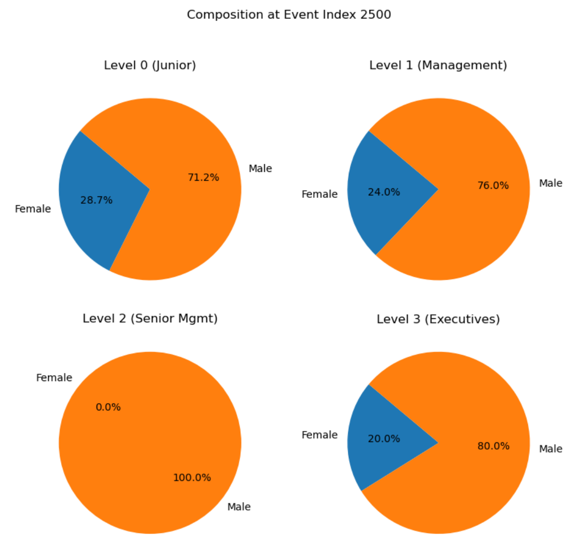

Figure 2: $t = 2500$

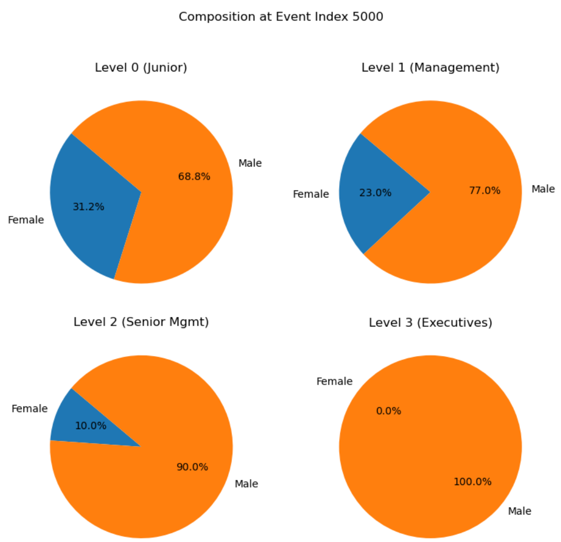

Figure 3: $t = 5000$

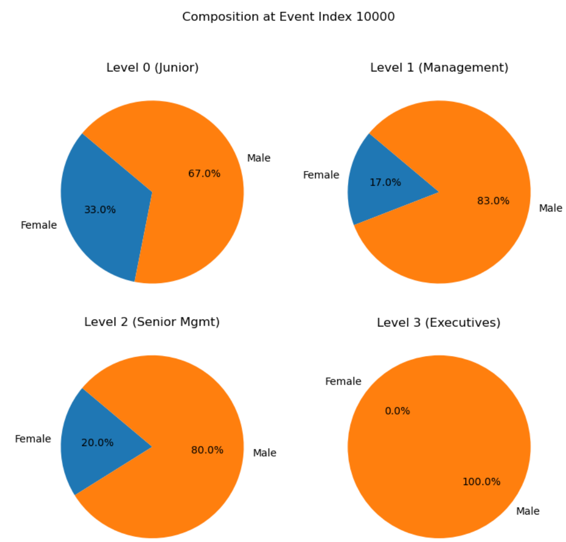

Figure 4: $t = 10000$

2 Main Body

2.1 Modeling Approach

2.1.1 Model Overview

We built a simulation model for a simplified "pipeline" representing employees through a company hierarchy. A company has levels ranging from entry-level positions consisting of junior employees up to a small executive team. At any given point, a fixed number of people occupy each level.

The model evolution is in continuous time. Some employees may leave the company at random times. This creates a vacancy. When a vacancy appears at the top entry level, a new hire is brought in from outside the company; when a vacancy appears at any higher level, someone is promoted from the below-level. We keep track of the identity of each employee (in this case, represented as female or male) and their career history (when they were hired, when they were promoted, etc.)

2.1.2 Key Parameters

A few sets of parameters drive this model: First, we specify the departure rates for each level and identity group; these define the frequency at which employees leave. For instance, one could have higher departure rates for junior employees to reflect greater turnover among less experienced staff. Second, we choose hiring weights, which define the probability that a new hire is female versus male. Third, we choose promotion weights that determine who will be chosen when a position at a higher level is to be filled. With these weights, we model balanced and biased hiring and promotion policies.

2.1.3 Simulation Scenarios

We picked these parameters to explore some questions about gender imbalance. For example, we could start with no equal hiring and promotion weights and then introduce a small difference-such as a slightly higher chance to hire or promote men just to see if this subtle shift can create large imbalances over time. We also vary the departure rates to examine whether some groups leaving more frequently can exacerbate or offset these imbalances. These parameters are simple, and therefore, running a lot of simulations and comparing the outcomes for different conditions is quite easy.

The model is reasonable in general since it captures the essential features of organizational dynamics-fixed hierarchy levels, constant vacancies filled by either new hires or promotions, and random departures-while being flexible enough to isolate the effects of small probability differences. Although it is less detailed than a real company might be, this level of abstraction enables us to focus on the key question: how do small biases in hiring or promotion rates accumulate over long periods, and what patterns emerge in the composition of a company's workforce?

2.2 Model Details

2.2.1 State Representation

We model the company as having four levels of employees, labeled $l = 0, 1, 2, 3$, where $l = 0$ is the entry-level and $l = 3$ is the top executive level. Each level l has a fixed number of employees, denoted by n_l. For this model, $n_0 = 400, n_1 = 100, n_2 = 20, n_3 = 5$. In addition, the company is categorized into two identity groups: female (F) and male (M).

At time t, the state $X(t)$ can be represented as the number of female and male employees at each level:

$$X(t) = \begin{pmatrix} X_{0,F}(t) & X_{0,M}(t) \\ X_{1,F}(t) & X_{1,M}(t) \\ X_{2,F}(t) & X_{2,M}(t) \\ X_{3,F}(t) & X_{3,M}(t) \end{pmatrix},$$

with the constraint that $X_{l,F}(t) + X_{l,M}(t) = n_l$ for each level l.

In our implementation, we track individual employees as objects, but the underlying logic is equivalent. The key point is that the system's state fully determines which events (departures, hires, promotions) can occur and at what rates.

2.2.2 Transitions

Employees leave the company randomly over time. Each employee's departure is governed by an exponential "clock" with a rate dependent on their level l and identity $i \in \{F, M\}$. Let $\lambda_{l,i}$ be the per-employee departure rate for employees at level l of identity i. If there are $X_{l,i}(t)$ such employees at time t, the total departure rate from that subgroup is $\lambda_{l,i} X_{l,i}(t)$.

Summing over all levels and identities, the total departure rate out of state $X(t)$ is:

$$R(X(t)) = \sum_{l=0}^{3} \sum_{i \in \{F,M\}} \lambda_{l,i} X_{l,i}(t).$$

A departure event occurs randomly according to $R(X(t))$, and we choose which employee departs with probability proportional to their subgroup's rate.

2.2.3 Hiring and Promotion Rules

After a departure, the company immediately fills the resulting vacancy. If the vacancy is at level 0, a new hire is brought in from outside. The probability that the new hire is female or male is determined by hiring weights $w_{0,F}$ and $w_{0,M}$:

$$P(\text{new hire is female}) = \frac{w_{0,F}}{w_{0,F} + w_{0,M}}, \quad P(\text{new hire is male}) = \frac{w_{0,M}}{w_{0,F} + w_{0,M}}.$$

If the vacancy is at level $l \geq 1$, it is filled by promoting an employee from level $(l-1)$. Let $X_{l-1,F}(t)$ and $X_{l-1,M}(t)$ be the counts at that level. Given promotion weights $w_{l,F}$ and $w_{l,M}$, the probability of promoting a female is:

$$P(\text{promote female from level } l-1) = \frac{w_{l,F} X_{l-1,F}(t)}{w_{l,F} X_{l-1,F}(t) + w_{l,M} X_{l-1,M}(t)},$$

and similarly for males. Among employees of the chosen identity, one is selected uniformly at random for the promotion.

2.2.4 Markov Property and Continuous-Time

Since departures occur at exponential times and the probabilities of the next event depend only on the current state, the system is a CTMC. The memory-less property of the exponential random variable ensures that at each state, we can compute $R(X(t))$, sample an exponential waiting time for the next departure, and then update the state accordingly.

Over a simulation run, we generate a sequence of events $(t_1, X(t_1)), (t_2, X(t_2)), \dots,$ where each event corresponds to a departure followed by a hire or promotion. This defines a piecewise-constant right-continuous path of the state over time.

2.2.5 Verification and Validation

To build confidence in the correctness of the implementation, we performed several checks:

1. **Simplified Cases:** We tested a one-level model (just $l = 0$) where the system becomes a simple birth-death process with known equilibrium distributions. Under this scenario, setting equal hiring probabilities and rates leads to stable proportions that match theoretical expectations, which are shown in Figure 1. In Figure 2, we slightly tune the $\lambda_{0F} = 0.03$ instead of $\lambda_{0i} = 0.01$; this slight disadvantage shows the overall decrease in women's employment at the initial level, showing the correct function of our model.

2. **No-Bias Scenario:** Setting all weights $w_{l,F} = w_{l,M}$ and $\lambda_{l,F} = \lambda_{l,M}$ for all levels l should produce no systematic drift in the fraction of females at each level over time. We confirmed empirically that the proportions remain stable. For Level 2 and Level 3, since the sample size is small, the fluctuation is expected to be large. However, we can examine that the fraction of women is approximately 50% in each case.

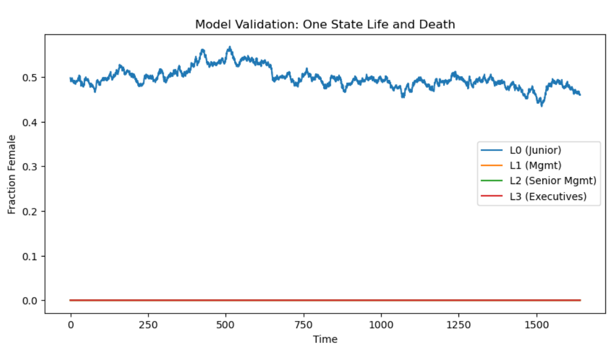

Figure 5: Simplified Cases: $L0$ with equal $w_{0i} = 1$ and $\lambda_{0i} = 0.01$

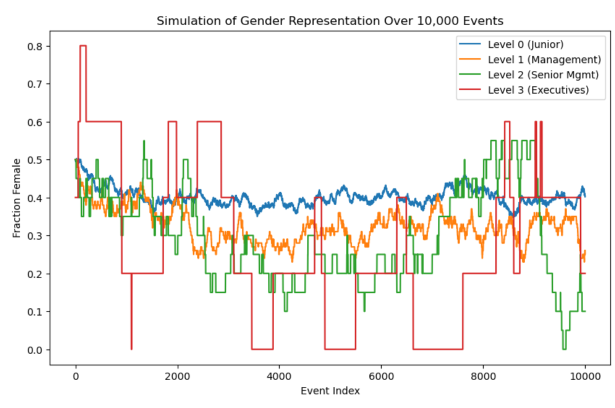

Figure 6: No-Bias Scenario: Same parameters (leave rate, weights, initial counts)

3. **Boundary Checks:** We verified that if all departure rates are zero, no events occur. If $w_{0,F} = 0$, the system never hires females at level 0, and indeed no female presence emerges after the initial configuration.

2.3 Model Analysis

To study the impact of gender bias, we simulated career trajectories under various bias scenarios. We are going to examine each question extensively.

1. How do varying departure rates—some groups leaving more frequently than others—interact with hiring and promotion biases to shape long-term gender composition at each level?

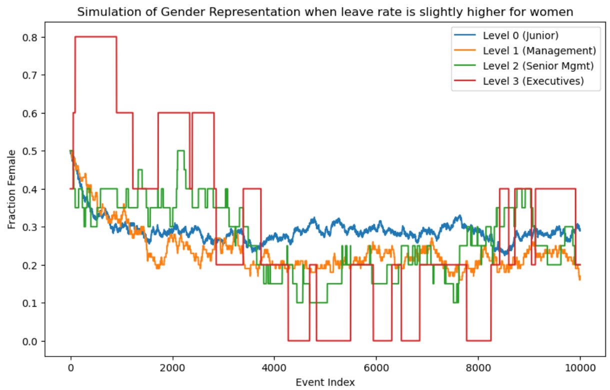

Figure 7: Stimulate slight higher leave rate for women: Tuning $\lambda_{l,F}$ to be slightly higher than $\lambda_{l,M}$. For example, let $\lambda_{l,F} = 0.02$ while $\lambda_{l,M} = 0.01$ and weights equal.

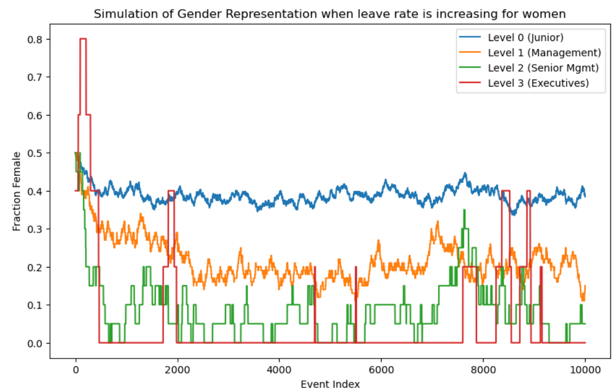

Figure 8: Stimulating increasing leave rate for women: $\lambda_{0,F} = 0.01$, $\lambda_{1,F} = 0.02$, $\lambda_{2,F} = 0.03$, $\lambda_{3,F} = 0.04$ while keeping weights equal.

Results: A small bias factor ($w_{l,F}$ for females) at early levels led to a reduction in female representation at leadership positions drastically. If we stimulate an increasing leave rate for women in the higher stages, the drop in a fraction of women is more drastic, as shown in Figure 4.

2. If women and men begin in equal numbers at the bottom, but promotions go just a bit more often to men, does this slight bias gradually develop into a large under-representation of women at the top?

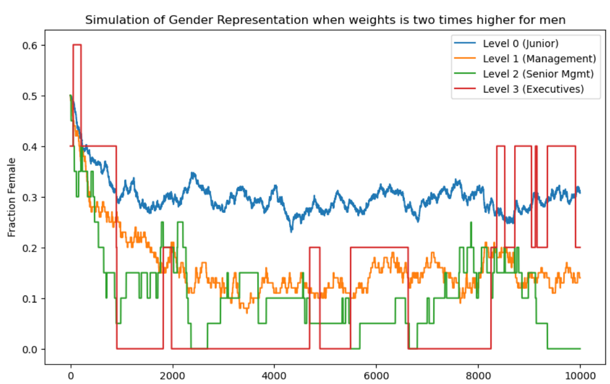

Figure 9: Stimulate men are twice as likely to get promoted compared to women

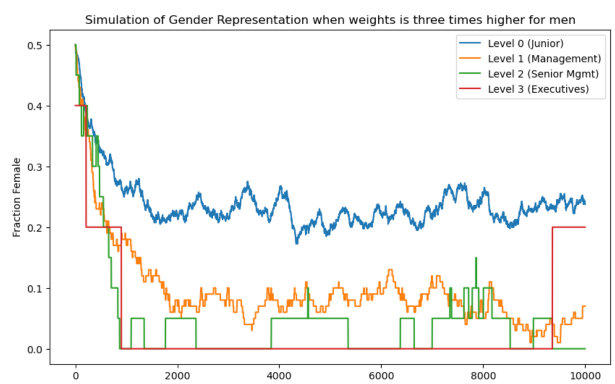

Figure 10: Stimulate men are three times more likely to get promoted compared to women

Results: The bias in the promotion can lead to a drastic loss of women workforce during the start of the model. Level 0 is given to be least affected. The count is stabilized at around 30% women. However, due to the higher promotion of men in both cases, we can see that the women's ratio stabilizes at a lower value for the two different weights for higher-level roles. For example, if men are three times more likely to get promoted. There will be generally less than 10% of women in Levels 1, 2, and 3.

3. How does gender bias impact career progression over time in hierarchical organizations? To examine this question, let's consider a series of conditions that are sequentially added:

- Figure 11: The company recruits 40% women and 60% men initially
- Figure 12: The company is 10% more likely to promote men compared to women in the first two stages.
- Figure 13: The company is 20% more likely to promote men compared to women in the final two stages.
- Figure 14: Women are 50% more likely to leave compared to a man

Results: As we negatively impact the women workforce using the constraints above, we can see the general shift of the curves downward. Given these constraints, in the long run, the women's presence in the company is generally around 35% in $L0$, 20% in $L1$, 10% in $L2$, and 20% in $L3$. These result strongly indicates that gender biases encourage gender imbalance in the workforce. These issues are going to be more severe in higher-level positions.

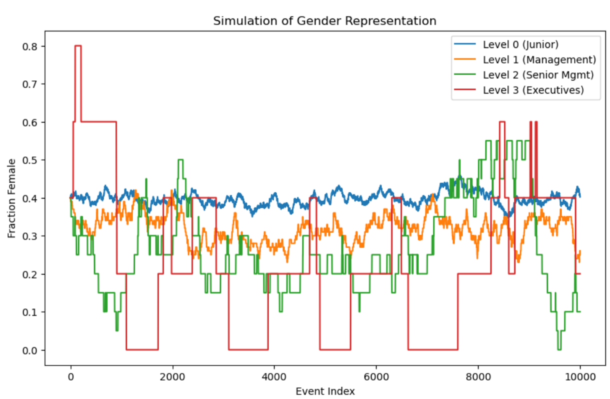

Figure 11

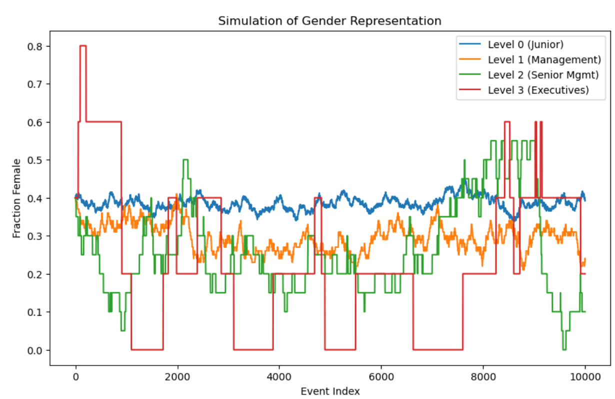

Figure 12

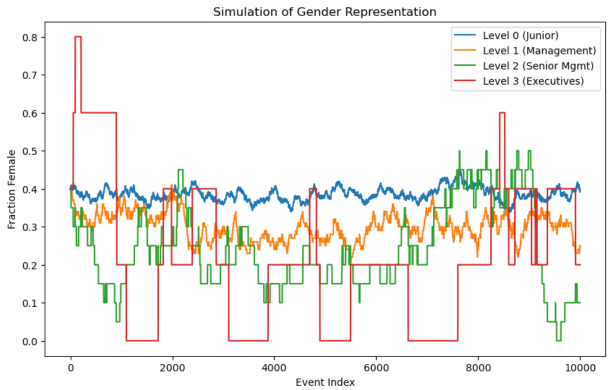

Figure 13

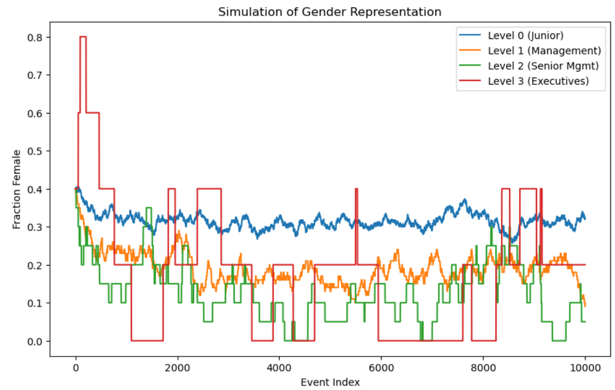

Figure 14

2.4 Conclusions

The study highlights the cumulative impact of gender bias on career progression. Imbalance recruiting ratio, differences in promotion rates, and disparate departure rates between men and women can have a significant impact on the gender equality of the company. These differences can build up over time, leading to further inequality in higher-level positions.

Recommendations include implementing interventions focused on early-career stages to mitigate long-term disparities.

- **Implement Transparent Promotion Criteria:** develop standardized promotion metrics to promote equality between men and women workers.
- Simulation Scenarios implement a flexible work schedule to discourage leaving. Incentivize parental leaves and support programs to support retention.
- **Establish Clear Diversity Goals:** regularly review progress and adjust strategies to meet these goals.
- **Encourage Employee Feedback:** create anonymous feedback channels where employees can share concerns about bias or inequality.

3 Technical Appendices

3.1 Simulation Algorithm

1. **Initialize the system**:
   - Define the hierarchical structure of the company with four levels: Junior (Level 0), Management (Level 1), Senior Management (Level 2), and Executives (Level 3).
   - Set the initial population size at each level and assign identities (Female or Male) to all employees.
   - Specify model parameters:
     - Hiring weights $w_{\ell,F}, w_{\ell,M}$.
     - Promotion weights $w_{\ell,F}, w_{\ell,M}$.
     - Departure rates $\lambda_{\ell,F}, \lambda_{\ell,M}$.
2. **Run the simulation**:
   - **While** the simulation has not reached the desired number of events or steady-state conditions:
     (a) **Compute transition rates**:
       - Calculate the departure rate for each subgroup (e.g., females or males at each level):
       $$R(X(t)) = \sum_{\ell=0}^{3} \sum_{i\in\{F,M\}} \lambda_{\ell,i} X_{\ell,i}(t).$$
       - Compute the total rate $R(X(t))$ for all possible events (departures, hires, promotions).

     (b) **Sample the next event**:
       - Draw the time to the next event Δt from an exponential distribution with rate $R(X(t))$.
       - Select which event occurs (departure, hire, or promotion) based on their probabilities.

     (c) **Update the state**:
       - If the event is a departure:
         * Identify the departing employee based on subgroup departure rates.
         * Remove the employee from the corresponding level.
       - If the event is a hire (Level 0):
         * Hire a new employee with a probability proportional to $w_{0,F}$ and $w_{0,M}$.
         * Add the new employee to Level 0.
       - If the event is a promotion (Level $\ell \geq 1$):
         * Promote an employee from Level $\ell - 1$ with a probability proportional to $w_{\ell,F}$ and $w_{\ell,M}$.
         * Move the promoted employee to Level ℓ.

     (d) **Record the state**:
       - Save the current gender composition of all levels for analysis.

3. **Terminate when the desired number of events or steady-state conditions is reached**:
   - Output the recorded gender composition data for further analysis.

Validation Steps

1. **Simplified Cases**:
   - Tested a one-level system ($\ell = 0$) with uniform hiring and departure rates. Confirmed equilibrium matches theoretical expectations from birth-death processes.
2. **No-Bias Scenario**:
   - Verified that equal hiring and promotion weights ($w_{\ell,F} = w_{\ell,M}$) and departure rates ($\lambda_{\ell,F} = \lambda_{\ell,M}$) resulted in stable gender proportions.
3. **Boundary Cases**:
   - Ensured no events occur when departure rates are zero.
   - Verified that $w_{\ell,F} = 0$ results in no females being hired or promoted.

Sensitivity Analysis

1. **Effect of Hiring Bias**:
   - Simulated scenarios with biased hiring weights (e.g., $w_{0,F}/w_{0,M} = 0.9$). Observed propagation of hiring biases to senior levels over time.
2. **Impact of Promotion Bias**:
   - Tested scenarios where promotion weights favored males (e.g., $w_{\ell,F}/w_{\ell,M} = 0.8$). Found that even small promotion biases led to significant disparities at higher levels.
3. **Departure Rates**:
   - Simulated higher female departure rates (e.g., $\lambda_{\ell,F} = 0.02$, $\lambda_{\ell,M} = 0.01$). Observed faster attrition of females, amplifying gender disparities.