Gender Wage Disparities in Clean Technology Manufacturing Sectors: A Mathematical Framework for Assessment and Policy Design

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Abstract

This paper develops a comprehensive mathematical framework to analyze and measure gender wage disparities in clean technology manufacturing sectors. We propose five novel indices that capture different dimensions of gender inequality in this emerging industry: the Gender Wage Gap Index (GWGI), Sectoral Gender Parity Index (SGPI), Occupational Segregation Coefficient (OSC), Technology-Skill Premium Gender Differential (TSPGD), and Clean Technology Gender Employment Quality Index (CTGEQI). Through an optimization-based theoretical model, we examine how technological change in sustainable manufacturing affects gender wage structures and derive policy implications for promoting equitable growth in green economies. Our analysis reveals that without targeted interventions, the transition to clean technology manufacturing may perpetuate or exacerbate existing gender wage gaps, particularly in high-skill technical positions. The proposed indicators provide policymakers and researchers with quantitative tools to monitor progress toward gender parity in this strategic sector for sustainable development.

Keywords: Gender wage gap, clean technology, manufacturing, optimization, inequality indices
JEL Classification: J31, J16, O33, Q55, C61

1 Introduction

The global transition toward sustainable energy systems and clean technology manufacturing represents one of the most significant economic transformations of the 21st century. As documented by **Ajagekar2022quantum<empty citation>** and **Ricciardi2024quantu** emerging technologies for renewable energy production, carbon capture, and sustainable materials require substantial investments in advanced manufacturing capabilities. This sectoral shift creates both opportunities and challenges for labor markets, particularly regarding gender equity in employment and compensation.

The clean technology manufacturing sector encompasses production of solar panels, wind turbines, electric vehicle components, energy storage systems, and advanced materials for carbon capture (**Paudel2022quantum**). These industries are characterized by rapid technological innovation, high capital intensity, and demand for specialized technical skills. Yet despite growing recognition of gender disparities in STEM fields and manufacturing more broadly (**frank2019toward**; **sultana2024macroeconomic**), systematic analysis of wage gaps specifically within clean technology sectors remains limited.

Existing literature on gender wage differentials has established several key findings. First, wage gaps persist across most economic sectors even after controlling for education, experience, and occupation (**webb2019impact**; **acemoglu2018artificial**). Second, technological change can have heterogeneous effects on gender inequality depending on how new technologies complement or substitute for different types of labor (**korinek2019artificial** **ernst2019economics**). Third, emerging industries often replicate or amplify existing labor market inequalities unless deliberate policy interventions are implemented (**cazzaniga2024genai** **jia2024social**).

The contribution of this paper is threefold. First, we develop a rigorous mathematical framework for analyzing gender wage determination in clean technology manufacturing that explicitly incorporates both supply-side factors (human capital, occupational sorting) and demand-side factors (employer preferences, technological complementarities). Second, we propose five complementary indices that capture distinct dimensions of gender wage disparities and can be operationalized using standard labor market data. Third, we derive optimal policy responses through a social planner's optimization problem that balances efficiency and equity objectives.

Our theoretical analysis yields several important results. We show that even under perfect competition and absence of taste-based discrimination, statistical discrimination and occupational segregation can generate persistent wage gaps in equilibrium. Furthermore, we demonstrate that technology-skill complementarities in clean manufacturing may disproportionately benefit male workers if gender gaps in technical education persist. The proposed indices enable decomposition of overall wage disparities into components attributable to human capital differences, occupational sorting, within-occupation gaps, and returns to technology-related skills.

The remainder of this paper proceeds as follows. Section 2 reviews relevant theoretical and empirical literature. Section 3 presents our mathematical model of gender wage determination in clean technology manufacturing. Section 4 introduces the five proposed inequality indices with formal definitions. Section 5 analyzes equilibrium properties and derives comparative statics. Section 6 discusses policy implications and optimal intervention design. Section 7 concludes.

2 Theoretical Framework and Literature

The analysis of gender wage disparities requires integration of insights from labor economics, industrial organization, and the economics of technological change. We build our framework on three main theoretical traditions.

2.1 Human Capital Theory and Wage Determination

The human capital approach pioneered by Becker and Mincer emphasizes that wage differentials reflect differences in productive capabilities acquired through education and experience. In this framework, gender wage gaps arise primarily from differences in human capital investments. However, as noted by **acemoglu2018race<empty citation>**, this explanation is incomplete because substantial unexplained gaps persist even after controlling for observable human capital characteristics.

Recent work by **schindler2021technological<empty citation>** extends human capital theory to account for rapid technological change. They show that returns to different types of skills evolve dynamically as new technologies emerge, potentially creating gender-differentiated impacts if men and women have different skill distributions or face different barriers to skill acquisition.

2.2 Discrimination and Labor Market Segmentation

Becker's theory of taste-based discrimination predicts that competitive markets should eliminate wage gaps arising from employer prejudice. However, as **acemoglu2018artificial<empty** demonstrates, statistical discrimination based on noisy signals of productivity can persist in equilibrium. Moreover, occupational segregation resulting from social norms, information asymmetries, or network effects can generate wage gaps even without explicit discrimination (**frank2019toward**).

The literature on labor market segmentation emphasizes that manufacturing sectors are often characterized by distinct internal labor markets with different wage-setting mechanisms (**katz2021impact**). Clean technology manufacturing may exhibit particular segmentation patterns due to the coexistence of traditional manufacturing skills and novel technical competencies.

2.3 Technology and Inequality

A growing body of research examines how technological change affects wage inequality. **korinek2017artificial<empty citation>** develop a framework showing that automation can have heterogeneous effects across demographic groups depending on which tasks are automated and how different workers' skills complement new technologies. **ernst2019economics<empty citation>** extend this analysis to gender disparities, showing that women may face particular risks from automation in routine cognitive tasks but may also benefit from new job creation in sectors requiring social and emotional skills.

For clean technology manufacturing specifically, **Paudel2022quantum<empty citation>** and **Ajagekar2022quantum<empty citation>** document that advanced manufacturing processes require combinations of traditional engineering skills and emerging technical competencies. The gender composition of workers with these skill combinations may differ substantially from overall gender representation in manufacturing, potentially affecting wage structures.

3 Mathematical Model

We develop a theoretical model of wage determination in clean technology manufacturing that incorporates both competitive and discriminatory elements. Consider an economy with a continuum of firms producing clean technology products using labor as the primary input.

3.1 Production Technology

Each firm i has a production function that combines male labor L_m^i and female labor L_f^i to produce output Y^i. We specify a CES production function that allows for imperfect substitutability between male and female labor:

$$Y^i = A \left[\alpha \left(\theta_m L_m^i\right)^\rho + (1-\alpha) \left(\theta_f L_f^i\right)^\rho\right]^{\frac{1}{\rho}} \tag{1}$$

where $A > 0$ is total factor productivity, $\alpha \in (0,1)$ governs the relative weight on male versus female labor, θ_m and θ_f are gender-specific human capital levels, and $\rho < 1$ determines the elasticity of substitution $\sigma = \frac{1}{1-\rho}$.

The parameter α captures potential differences in how male and female labor enter the production process. If $\alpha = 0.5$ and $\theta_m = \theta_f$, the production function treats both genders symmetrically. Deviations from symmetry can arise from occupational segregation or differences in average human capital.

3.2 Firm Optimization

Firms choose employment levels to maximize profits given competitive output markets and gender-specific wages w_m and w_f. The profit maximization problem is:

$$\max_{L_m^i, L_f^i} \pi^i = pY^i - w_m L_m^i - w_f L_f^i \tag{2}$$

where p is the output price, normalized to unity. First-order conditions yield:

$$w_m = A\alpha\theta_m^\rho \left[\alpha \left(\theta_m L_m^i\right)^\rho + (1-\alpha)\left(\theta_f L_f^i\right)^\rho\right]^{\frac{1-\rho}{\rho}} \left(L_m^i\right)^{\rho-1} \tag{3}$$

$$w_f = A(1-\alpha)\theta_f^\rho \left[\alpha \left(\theta_m L_m^i\right)^\rho + (1-\alpha)\left(\theta_f L_f^i\right)^\rho\right]^{\frac{1-\rho}{\rho}} \left(L_f^i\right)^{\rho-1} \tag{4}$$

Taking the ratio of these conditions:

$$\frac{w_m}{w_f} = \frac{\alpha}{1-\alpha}\left(\frac{\theta_m}{\theta_f}\right)^\rho \left(\frac{L_m^i}{L_f^i}\right)^{\rho-1} \tag{5}$$

This expression shows that the wage ratio depends on three factors: the production function parameter α, the human capital ratio θ_m/θ_f, and the employment ratio L_m^i/L_f^i. The elasticity of substitution σ affects how strongly relative wages respond to changes in relative employment.

3.3 Labor Supply and Equilibrium

On the supply side, we assume total labor supplies $\bar{L}_m$ and $\bar{L}_f$ are fixed in the short run but that human capital accumulation responds to wage incentives in the long run. Let $\theta_g = h_g(e_g)$ for $g \in \{m, f\}$, where e_g is education investment and $h_g(\cdot)$ is an increasing, concave function.

Workers choose education levels to maximize lifetime utility:

$$\max_{e_g} V_g = w_g h_g(e_g) - c_g(e_g) \tag{6}$$

where $c_g(e_g)$ is the cost of education, which may differ by gender due to social barriers, financing constraints, or opportunity costs. The optimal education choice satisfies:

$$w_g h_g'(e_g^*) = c_g'(e_g^*) \tag{7}$$

Market equilibrium requires labor market clearing:

$$\int_0^1 L_m^i di = \bar{L}_m, \quad \int_0^1 L_f^i di = \bar{L}_f \tag{8}$$

and zero-profit conditions for free entry.

Proposition 1. *Under perfect competition with symmetric production parameters* ($\alpha = 0.5$) *and equal human capital costs* ($c_m = c_f$)*, equilibrium exhibits no gender wage gap if and only if initial human capital levels are equal* ($\theta_m = \theta_f$)*.*

This proposition establishes that even in a competitive environment without taste-based discrimination, wage gaps arise from human capital differences. Moreover, if education costs differ by gender, gaps persist even with symmetric production technology.

3.4 Incorporating Discrimination

We extend the model to include employer discrimination following the statistical discrimination framework. Suppose firms observe noisy signals s_g of worker productivity with $s_g = \theta_g + \epsilon_g$, where $\epsilon_g \sim N(0, \sigma_g^2)$ is measurement error. If $\sigma_m^2 < \sigma_f^2$, female productivity is measured with more noise.

Risk-averse firms facing uncertainty about worker productivity will offer wages:

$$w_g = E[\theta_g | s_g] = \mu_g + \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_g^2}(s_g - \mu_g) \tag{9}$$

where $\mu_g = E[\theta_g]$ and σ_θ^2 is the variance of true productivity. This implies that even if $\mu_m = \mu_f$, average wages will differ if signal quality differs: workers from the group with noisier signals receive wages that regress more toward the group mean.

Lemma 1. *If* $\sigma_f^2 > \sigma_m^2$*, then average female wages are lower than average male wages even when true average productivity is equal, provided that the variance of productivity* $\sigma_\theta^2 > 0$*.*

This result captures how information asymmetries and statistical discrimination contribute to wage gaps independently of actual productivity differences.

4 Proposed Inequality Indices

We now introduce five indices designed to capture distinct dimensions of gender wage disparities in clean technology manufacturing. Each index is formally defined and operationalized using observable labor market data.

4.1 Gender Wage Gap Index (GWGI)

The Gender Wage Gap Index measures the unconditional wage differential between male and female workers:

$$GWGI = 1 - \frac{\bar{w}_f}{\bar{w}_m} \tag{10}$$

where $\bar{w}_m$ and $\bar{w}_f$ are average wages for male and female workers respectively. This index ranges from $-\infty$ to 1, with $GWGI = 0$ indicating perfect wage equality, positive values indicating male wage premium, and negative values indicating female wage premium.

The GWGI can be decomposed into explained and unexplained components using a Oaxaca-Blinder framework:

$$GWGI = \underbrace{\beta_m' \left(\bar{X}_m - \bar{X}_f\right)}_{\text{Explained}} + \underbrace{\bar{X}_f' \left(\beta_m - \beta_f\right)}_{\text{Unexplained}} \tag{11}$$

where X denotes worker characteristics, β denotes returns to characteristics, and bars indicate group averages. The explained component reflects differences in observable human capital, while the unexplained component captures discrimination and unobserved factors.

4.2 Sectoral Gender Parity Index (SGPI)

The Sectoral Gender Parity Index measures how close the gender composition of clean technology manufacturing employment is to population parity:

$$SGPI = 1 - \left| \frac{L_f}{L_f + L_m} - 0.5 \right| \times 2 \tag{12}$$

This index ranges from 0 to 1, with $SGPI = 1$ indicating perfect parity (50% female, 50% male) and $SGPI = 0$ indicating complete gender segregation. Unlike the GWGI, the SGPI focuses on representation rather than compensation.

For finer analysis, we can define occupation-specific SGPI values:

$$SGPI_j = 1 - \left| \frac{L_{f,j}}{L_{f,j} + L_{m,j}} - 0.5 \right| \times 2 \tag{13}$$

where j indexes occupations within clean technology manufacturing. The aggregate SGPI is then:

$$SGPI = \sum_j \omega_j SGPI_j \tag{14}$$

where ω_j is the employment share of occupation j.

4.3 Occupational Segregation Coefficient (OSC)

The Occupational Segregation Coefficient quantifies the degree to which men and women work in different occupations within the sector. We use the Duncan dissimilarity index:

$$OSC = \frac{1}{2} \sum_{j=1}^{J} \left| \frac{L_{m,j}}{L_m} - \frac{L_{f,j}}{L_f} \right| \tag{15}$$

The OSC ranges from 0 to 1, where 0 indicates no segregation (men and women have identical occupational distributions) and 1 indicates complete segregation (no occupation has both male and female workers). The OSC can be interpreted as the proportion of workers who would need to change occupations to achieve perfect integration.

4.4 Technology-Skill Premium Gender Differential (TSPGD)

This index captures differences in returns to technology-related skills between male and female workers. Let $w_g(S)$ be the wage function for gender g as a function of technology skill level S. The TSPGD is defined as:

$$TSPGD = \frac{\partial w_m / \partial S}{\partial w_f / \partial S} - 1 \tag{16}$$

Operationally, this can be estimated by running Mincer regressions separately by gender:

$$\ln w_{gi} = \beta_{g0} + \beta_{g1} S_i + \beta_{g2} X_i + \epsilon_{gi} \tag{17}$$

and computing:

$$TSPGD = \frac{\beta_{m1}}{\beta_{f1}} - 1 \tag{18}$$

Positive values of TSPGD indicate that male workers receive higher wage returns to technology skills than female workers with equivalent skill levels. This index is particularly relevant for clean technology manufacturing where technical competencies command premium wages.

4.5 Clean Technology Gender Employment Quality Index (CTGEQI)

The CTGEQI provides a composite measure incorporating multiple dimensions of employment quality beyond wages. We define:

$$CTGEQI = 1 - \sqrt{\sum_{k=1}^{K} \gamma_k \left(I_{m,k} - I_{f,k}\right)^2} \tag{19}$$

where $I_{g,k}$ denotes the k-th employment quality indicator for gender g, K is the total number of indicators, and γ_k are weights satisfying $\sum_k \gamma_k = 1$. Relevant indicators include:

- Wage levels (captured by inverse GWGI)
- Access to benefits (health insurance, retirement plans)
- Job security (permanent vs temporary contracts)
- Career advancement opportunities
- Training and skill development access

The CTGEQI ranges from 0 to 1, with higher values indicating greater gender equality in overall employment quality.

5 Equilibrium Analysis and Policy Implications

We now analyze equilibrium properties of the model and derive policy implications for reducing gender wage disparities in clean technology manufacturing.

5.1 Comparative Statics

Consider how changes in key parameters affect equilibrium wage gaps. From equation (5), the wage ratio satisfies:

$$\ln\left(\frac{w_m}{w_f}\right) = \ln\left(\frac{\alpha}{1-\alpha}\right) + \rho \ln\left(\frac{\theta_m}{\theta_f}\right) + (\rho - 1)\ln\left(\frac{L_m}{L_f}\right) \tag{20}$$

Taking derivatives:

$$\frac{\partial \ln(w_m/w_f)}{\partial \theta_m} = \frac{\rho}{\theta_m} > 0 \tag{21}$$

$$\frac{\partial \ln(w_m/w_f)}{\partial \alpha} = \frac{1}{\alpha(1-\alpha)} > 0 \tag{22}$$

$$\frac{\partial \ln(w_m/w_f)}{\partial \rho} = \ln\left(\frac{\theta_m}{\theta_f}\right) + \ln\left(\frac{L_m}{L_f}\right) \tag{23}$$

These results show that the wage gap increases with male human capital, with production function asymmetry favoring male labor, and ambiguously with the elasticity of substitution depending on whether human capital or employment ratios dominate.

Proposition 2. *If $\theta_m > \theta_f$ and $L_m > L_f$, then reducing the elasticity of substitution σ (increasing $|\rho|$) amplifies the wage gap.*

This proposition has important implications for technological change in clean technology manufacturing. If new production technologies make male and female labor less substitutable (lower σ), existing gaps may widen. Conversely, technologies that increase substitutability could reduce gaps even without changes in human capital or employment ratios.

5.2 Policy Instruments

We consider three types of policy interventions: human capital policies, anti-discrimination enforcement, and affirmative action in hiring. Let τ denote a policy parameter representing intervention intensity.

Human Capital Subsidies: Suppose the government subsidizes female education at rate s_f, reducing effective education costs to $c_f(e_f)(1-s_f)$. The optimal education choice becomes:

$$w_f h_f'(e_f^*) = c_f'(e_f^*)(1-s_f) \tag{24}$$

implying higher female education investment for $s_f > 0$. In equilibrium, this increases θ_f, reducing the wage gap. The optimal subsidy rate balances fiscal costs against inequality reduction:

$$\max_{s_f} W = U(w_m, w_f, GWGI) - C(s_f) \tag{25}$$

where W is social welfare, U increases in wages and decreases in GWGI, and C is the fiscal cost function.

Anti-Discrimination Enforcement: Let τ represent enforcement intensity, with firms facing expected penalties $F(\tau)$ if found discriminating. This modifies the firm's problem to:

$$\max_{L_m, L_f} \pi = pY - w_m L_m - w_f L_f - F(\tau)\mathbb{1}[\text{discrimination}] \tag{26}$$

where $\mathbb{1}[\cdot]$ is an indicator function. Stronger enforcement reduces discriminatory wage gaps by increasing expected costs of discrimination.

Affirmative Action: Hiring mandates require firms to maintain $L_f/(L_f + L_m) \geq \phi$ for some target ϕ. This constraint binds when market outcomes would yield lower female representation. The constrained optimization problem is:

$$\max_{L_m, L_f} \pi \quad \text{s.t.} \quad L_f \geq \phi(L_f + L_m) \tag{27}$$

Using the Lagrangian method:

$$\mathcal{L} = pY - w_m L_m - w_f L_f + \lambda[L_f - \phi(L_f + L_m)] \tag{28}$$

First-order conditions yield modified labor demand curves incorporating the shadow value λ of the hiring constraint.

5.3 Optimal Policy Mix

A social planner seeking to minimize wage disparities subject to budget constraints solves:

$$\min_{s_f, \tau, \phi} GWGI(s_f, \tau, \phi) + \gamma_1 OSC(s_f, \tau, \phi) + \gamma_2(1 - SGPI(s_f, \tau, \phi)) \tag{29}$$

subject to:

$$B(s_f) + E(\tau) \leq \bar{B} \tag{30}$$

where $B(\cdot)$ is the cost of education subsidies, $E(\cdot)$ is the cost of enforcement, $\bar{B}$ is the total budget, and γ_1, γ_2 are weights on segregation and representation objectives.

Theorem 1. *Under convex costs and concave objectives, the optimal policy mix involves positive levels of all three instruments* ($s_f^* > 0, \tau^* > 0, \phi^* > 0$) *unless one instrument is strictly dominated.*

This result implies that comprehensive policy approaches combining multiple instruments are typically superior to single-instrument policies. Human capital subsidies address supply-side gaps, enforcement reduces discrimination, and affirmative action counters occupational segregation.

6 Discussion and Extensions

Our framework and proposed indices enable several important extensions and applications relevant for clean technology manufacturing sectors.

6.1 Dynamic Considerations

The static model can be extended to analyze dynamic wage gaps over the lifecycle. Let t index career stage and allow human capital to evolve:

$$\theta_{gt} = \theta_{g,t-1}(1-\delta) + I_{gt} \tag{31}$$

where δ is depreciation and I_{gt} is investment in skill upgrading. Gender differences in training access or career interruptions affect human capital trajectories, potentially widening wage gaps over time even if entry-level gaps are small.

6.2 Technological Change

Clean technology manufacturing undergoes rapid technological change, which affects both the production function and skill requirements. Let A_t represent the state of technology at time t. Skill-biased technological change can be modeled as:

$$\frac{\partial \ln(w_m/w_f)}{\partial A_t} = \frac{\partial \rho}{\partial A_t}\left[\ln\left(\frac{\theta_m}{\theta_f}\right) + \ln\left(\frac{L_m}{L_f}\right)\right] \tag{32}$$

If technological advances reduce substitutability ($\partial\rho/\partial A_t < 0$) and $\theta_m > \theta_f$, then technical progress widens wage gaps. This mechanism is particularly relevant for emerging quantum technologies and advanced manufacturing processes that may favor workers with specific technical backgrounds.

6.3 Intersectionality

The framework can incorporate intersectional dimensions by introducing additional worker characteristics. Let R denote race/ethnicity and consider wages w_{gr} for gender-race combinations. The wage gap decomposition becomes:

$$GWGI_{gr} = 1 - \frac{w_{fr}}{w_{mr}} \tag{33}$$

with intersectional effects captured by:

$$IE_r = GWGI_{gr} - GWGI \tag{34}$$

where $IE_r > 0$ indicates that gender gaps are larger within racial group r than overall.

6.4 Firm Heterogeneity

Firms differ in size, technology, and organizational practices. Let Ω_i denote firm i's characteristics. Wage gaps may vary across firms:

$$GWGI_i = g(\Omega_i, \theta_m, \theta_f, \alpha_i) \tag{35}$$

Empirically, larger firms and those with more advanced technologies may exhibit different wage gap patterns. This heterogeneity suggests that sector-wide policies should account for firm-level variation.

6.5 International Dimensions

Clean technology manufacturing increasingly involves global supply chains. Consider a two-country model where country $c \in \{1, 2\}$ has wage gap $GWGI_c$. Trade integration affects domestic wage gaps through:

$$\frac{\partial GWGI_1}{\partial \text{Trade}} = \frac{\partial GWGI_1}{\partial L_{f1}} \frac{\partial L_{f1}}{\partial \text{Trade}} \tag{36}$$

Trade may reduce or exacerbate gender wage gaps depending on whether exporting sectors are female-intensive and whether trade affects returns to skills differentially by gender. As documented by **Saranya2025review<empty citation>**, developing countries entering clean technology manufacturing may face particular challenges in ensuring equitable outcomes during industrialization.

7 Conclusion

This paper has developed a comprehensive mathematical framework for analyzing gender wage disparities in clean technology manufacturing sectors. We proposed five complementary indices (GWGI, SGPI, OSC, TSPGD, CTGEQI) that capture different dimensions of inequality and can guide both research and policy.

Our theoretical analysis demonstrates that wage gaps arise from multiple sources: human capital differences, occupational segregation, statistical discrimination, and technology-skill complementarities. Even competitive markets may generate persistent disparities in the absence of targeted interventions. The proposed optimization-based framework for policy design shows that comprehensive approaches combining education subsidies, anti-discrimination enforcement, and affirmative action are generally superior to single-instrument policies.

Several key findings emerge from our analysis. First, the transition to clean technology manufacturing risks perpetuating existing labor market inequalities if proactive policies are not implemented. Women remain underrepresented in technical fields that will be crucial for this sector, potentially leading to both employment gaps and wage gaps. Second, as **Ajagekar2022quantum<empty citation>** and **Paudel2022quantum<empty citation>** emphasize, emerging technologies in sustainable manufacturing may have skill-biased effects that disproportionately benefit workers with specific technical backgrounds, which could widen gender gaps if educational investments are not equitable. Third, the measurement framework we propose enables systematic monitoring of progress toward gender parity and identification of specific barriers requiring policy attention.

The practical implications for policymakers are clear. Countries and regions seeking to develop competitive clean technology manufacturing sectors should integrate gender equity objectives into industrial policy from the outset. This requires coordinated investments in education and training to build gender-balanced pools of qualified workers, enforcement mechanisms to prevent discriminatory practices, and potentially temporary measures to correct historical underrepresentation in key occupations.

For researchers, the proposed indices provide quantitative tools for empirical analysis. Future work should apply these measures to firm-level and administrative data to document actual wage gap magnitudes and trends. Cross-country comparisons using standardized indices could reveal best practices and policy lessons. Intersectional analyses incorporating race, ethnicity, and other dimensions would provide more complete understanding of inequality patterns.

Several limitations warrant acknowledgment. Our framework focuses primarily on wage disparities and does not fully address other forms of workplace inequality such as harassment, career advancement barriers, or work-family balance challenges. The model assumes competitive labor markets, whereas real-world clean technology manufacturing may involve significant monopsony power or institutional constraints on wage determination. Finally, we abstract from macroeconomic dynamics and business cycle effects that could interact with gender wage gaps in important ways.

Despite these limitations, we believe the analytical framework and proposed indices represent significant advances in the study of gender inequality in emerging sustainable industries. As the global economy continues its transition toward clean technology, ensuring that this transformation promotes rather than undermines gender equity should be a central policy priority. The tools developed in this paper can support evidence-based policymaking toward that objective.

References