Quota-Plus: A Computational Voting Mechanism for Fair Refugee Allocation

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October 2025

GitHub Repository: `https://github.com/aianniezhou-0529/COMPSCI-ECON-206-Final-Research-Proposal`

1. Contribution to Sustainable Development Goals (SDGs)

This research contributes to three key United Nations Sustainable Development Goals: SDG 10 (*Reduced Inequalities*), SDG 16 (*Peace, Justice, and Strong Institutions*), and SDG 17 (*Partnerships for the Goals*). The proposed *Quota-Plus* mechanism provides a computationally grounded solution to one of the most pressing global governance challenges—the fair allocation of refugees across European Union member states. By integrating fairness-oriented optimization, flexible compliance options, and transparent auditing tools, the design addresses both the efficiency and legitimacy dimensions of policy implementation.

2. Acknowledgments

I would like to express my deepest gratitude to Professor Luyao Zhang for her visionary guidance, intellectual generosity, and constant encouragement throughout the course. Her emphasis on interdisciplinary thinking between economics, computation, and ethics shaped both the theoretical foundation and empirical design of this project. I am also indebted to my classmates for their insightful peer feedback and active collaboration during coding labs and classroom simulations, which significantly improved the reproducibility and robustness of my analysis. Moreover, I acknowledge the open-source communities behind `NashPy`, `Game Theory Explorer (GTE)`, and `oTree`, whose tools made it possible to implement complex game-theoretic models in accessible computational environments. The assistance of advanced AI tools such as GPT-4 and Deepseek was also invaluable in facilitating large-scale data interpretation, simulation reasoning, and language refinement.

3. Disclaimer

This project is the final research proposal submitted to **COMPSCI/ECON 206: Computational Microeconomics**, instructed by Professor Luyao Zhang at Duke Kunshan University in Autumn 2025.

4. Statement of Intellectual and Professional Growth

Through this project, I strengthened my ability to connect economic theory, computational modeling, and policy-oriented mechanism design. By integrating game theory, algorithmic simulations, and institutional innovation, I developed greater mastery of interdisciplinary research design and Python-based experimentation. This experience improved my analytical thinking, teamwork, and communication skills, preparing me to apply computational social science methods to address global challenges in fairness, governance, and sustainable cooperation.

1 Strategic Game Foundations

1.1 Motivation and Background

This part establishes the foundation for rational strategic interaction through the **Subgame Perfect Nash Equilibrium (SPNE)**. SPNE ensures that each player's strategy is optimal in the full game and in every subgame, providing a baseline for analyzing rationality and credibility in sequential decision-making. These principles later inform the design of fair and stable allocation mechanisms in Part 3.

1.2 Definition (Paraphrased)

Let an extensive-form game with perfect information be

$$\Gamma = \langle N, H, P, (A(h))_{h \in H}, (u_i)_{i \in N} \rangle,$$

with N players, histories H, actions $A(h)$, and payoffs u_i. A **strategy** s_i specifies an action at every decision node of player i. A **strategy profile** $s = (s_1, \ldots, s_n)$ is an SPNE if, in every subgame $\Gamma(h)$,

$$u_i(s^*|_h) \geq u_i(s_i, s^*_{-i}|_h), \quad \forall i, s_i.$$

1.3 Existence and Backward Induction

For finite games with perfect information, SPNE always exists. Backward induction constructs SPNE by choosing optimal actions at terminal nodes and recursively moving backward, ensuring rationality in every subgame.

1.4 Analytical and Computational Interpretation

SPNE refines standard Nash equilibrium, ensuring consistency across all stages of play. It may not guarantee social optimality, highlighting trade-offs between individual rationality and collective welfare.

Empirically, humans and AI often deviate due to bounded rationality or social preferences. Computational tools such as `NashPy` and `GTE` verify equilibria and simulate strategic behavior, providing both theoretical and diagnostic insight.

1.5 Computational Scientist: Trust Simple

We operationalize SPNE using a one-round Trust Game. This micro-level simulation provides a foundation for the *Quota-Plus* mechanism, where equilibrium logic ensures incentive-compatible compliance.

$$u(A) = 100 - x + y$$

$$u(B) = 3x - y$$

Player A/B	0 %	50 %	100 %
0	(100,0)	(100,0)	(100,0)
50	(50,100)	(125,75)	(200,0)
100	(0,300)	(150,150)	(300,0)

Figure 1: Payoff matrix of the Trust Simple game.

```
Requirement already satisfied: nashpy in /usr/local/lib/python3.12/dist-packages (0.0.41)
Requirement already satisfied: numpy>=1.21.0 in /usr/local/lib/python3.12/dist-packages (from nashpy) (2.0.2)
Requirement already satisfied: scipy>=0.19.0 in /usr/local/lib/python3.12/dist-packages (from nashpy) (1.16.1)
Requirement already satisfied: networkx>=3.0.0 in /usr/local/lib/python3.12/dist-packages (from nashpy) (3.5)
Requirement already satisfied: deprecated>=1.2.14 in /usr/local/lib/python3.12/dist-packages (from nashpy) (1.2.18)
Requirement already satisfied: wrapt<2,>=1.10 in /usr/local/lib/python3.12/dist-packages (from deprecated>=1.2.14->nashpy) (1.17.3)
Normal-form Trust Game (Multiplier=3):
Bi matrix game with payoff matrices:

Row player:
[[100 100 100]
 [ 50 125 200]
 [  0 150 300]]

Column player:
[[  0   0   0]
 [150  75   0]
 [300 150   0]]

Nash Equilibria (pure and mixed strategies):
Player A strategy: [1. 0. 0.]
Player B strategy: [1. 0. 0.]
---
```

Figure 2: Nash Equilibria calculated by `NashPy` using Google Colab.

1.6 Interpretation

Figures 1–2 show that the SPNE is (0,0): Player A invests 0, Player B returns 0. Backward induction and computational analysis are consistent, validating the model and its applicability to multi-actor allocation problems.

1.7 Game Theory Explorer (GTE)

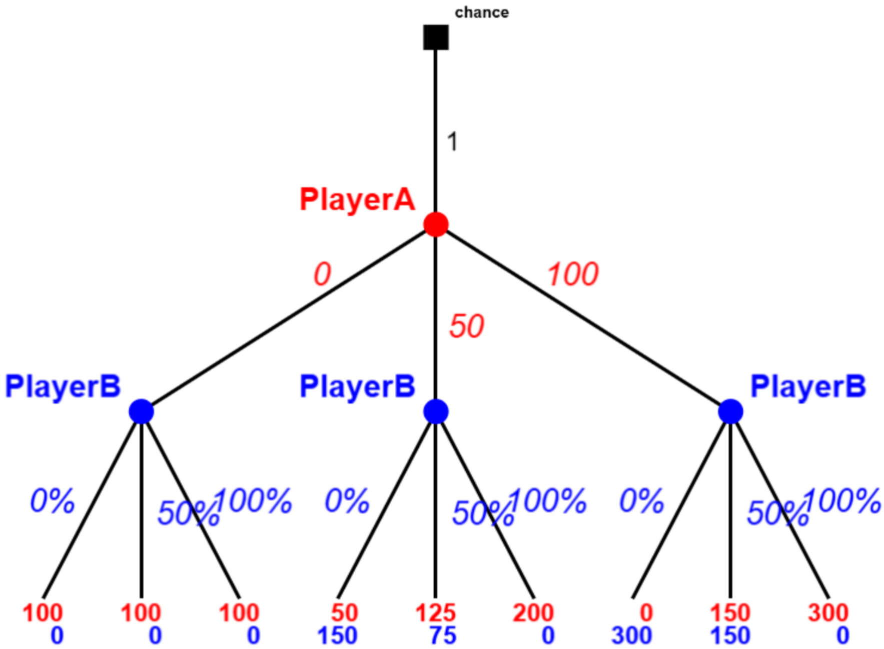

Figure 3: Extensive-form representation of the one-round Trust Game in GTE.

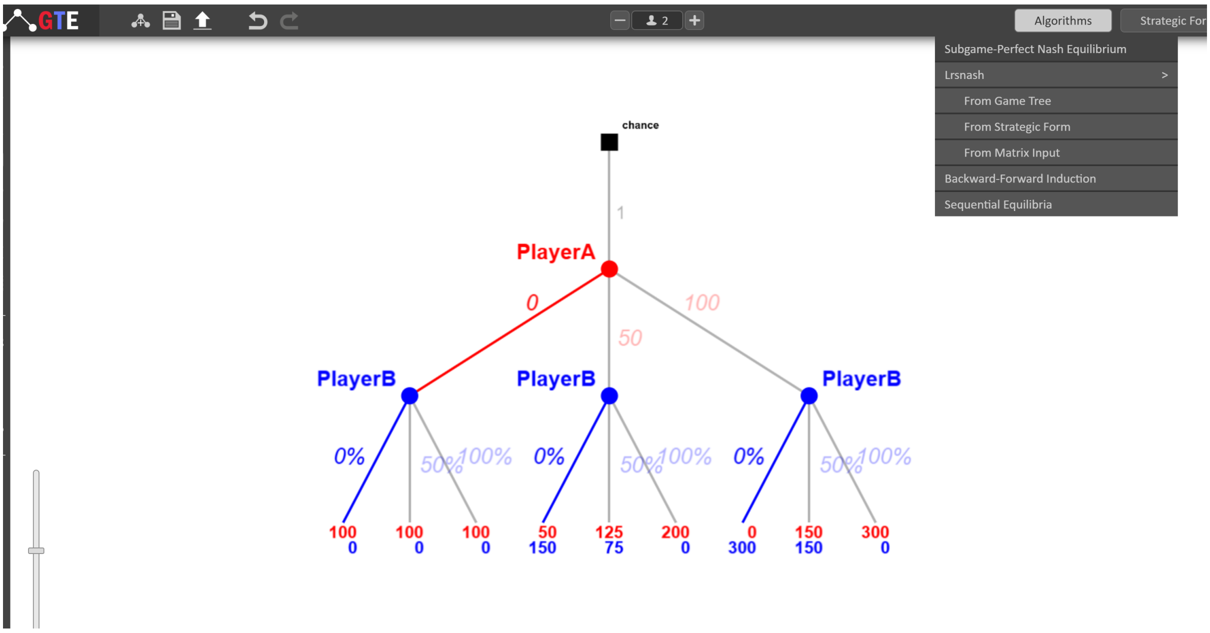

Figure 4: Solving the extensive-form Trust Simple with SPNE in GTE.

```
Solver

3 x 27 payoff matrix A:
  100  100  100  100  100  100  100  100  100  100  100  100  100  100  100  100  100  100  100  100  100  100  100  100  100  100  100
   50   50   50  125  125  125  200  200  200   50   50   50  125  125  125  200  200  200   50   50   50  125  125  125  200  200  200
    0  150  300    0  150  300    0  150  300    0  150  300    0  150  300    0  150  300    0  150  300    0  150  300    0  150  300

3 x 27 payoff matrix B:
    0    0    0    0    0    0    0    0 0    0    0    0    0    0  0    0    0 0    0    0    0    0    0  0    0    0 0
  150  150  150   75   75  75    0    0 0  150  150  150   75   75 75    0    0 0  150  150  150   75   75 75    0    0 0
  300  150    0  300  150   0  300  150 0  300  150    0  300  150  0  300  150 0  300  150    0  300  150  0  300  150 0

EE = Extreme Equilibrium, EP = Expected Payoff
Decimal Output
  EE    1  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:   (1)  1.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.
  EE    2  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:   (2)  0.333333  0.666667  0.000000  0.000000  0.000000  0.000000  0.
  EE    3  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:   (3)  0.000000  0.666667  0.000000  0.333333  0.000000  0.000000  0.
  EE    4  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:   (4)  0.000000  0.666667  0.000000  0.000000  0.000000  0.000000  0.
  EE    5  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:   (5)  0.000000  0.666667  0.000000  0.000000  0.000000  0.000000  0.
  EE    6  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:   (6)  0.000000  0.666667  0.000000  0.000000  0.000000  0.000000  0.
  EE    7  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:   (7)  0.000000  0.666667  0.000000  0.000000  0.000000  0.000000  0.
  EE    8  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:   (8)  0.000000  0.666667  0.000000  0.000000  0.000000  0.000000  0.
  EE    9  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:   (9)  0.000000  0.666667  0.000000  0.000000  0.000000  0.000000  0.
  EE   10  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (10)  0.000000  0.666667  0.000000  0.000000  0.000000  0.000000  0.
  EE   11  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (11)  0.666667  0.000000  0.333333  0.000000  0.000000  0.000000  0.
  EE   12  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (12)  0.000000  0.000000  0.333333  0.666667  0.000000  0.000000  0.
  EE   13  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (13)  0.333333  0.000000  0.333333  0.000000  0.000000  0.000000  0.
  EE   14  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (14)  0.000000  0.000000  0.333333  0.000000  0.000000  0.000000  0.
  EE   15  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (15)  0.000000  0.000000  0.333333  0.000000  0.000000  0.000000  0.
  EE   16  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (16)  0.500000  0.000000  0.166667  0.000000  0.000000  0.000000  0.
  EE   17  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (17)  0.000000  0.000000  0.166667  0.000000  0.000000  0.000000  0.
  EE   18  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (18)  0.000000  0.000000  0.166667  0.000000  0.000000  0.000000  0.
  EE   19  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (19)  0.000000  0.000000  0.333333  0.000000  0.000000  0.000000  0.
  EE   20  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (20)  0.000000  0.000000  0.333333  0.000000  0.000000  0.000000  0.
  EE   21  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (21)  0.333333  0.000000  0.333333  0.000000  0.000000  0.000000  0.
  EE   22  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (22)  0.000000  0.000000  0.333333  0.000000  0.000000  0.000000  0.
  EE   23  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (23)  0.000000  0.000000  0.333333  0.000000  0.000000  0.000000  0.
  EE   24  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (24)  0.500000  0.000000  0.166667  0.000000  0.000000  0.000000  0.
  EE   25  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (25)  0.000000  0.000000  0.166667  0.000000  0.000000  0.000000  0.
  EE   26  P1:  (1)  1.000000  0.000000  0.000000  EP=  100.0  P2:  (26)  0.000000  0.000000  0.166667  0.000000  0.000000  0.000000  0.
```

Figure 5: Alternative GTE solution path using the payoff matrix representation.

GTE confirms that backward induction leads to (0,0) equilibrium. SPNE provides a predictive framework for more complex institutional mechanisms, motivating *Quota-Plus*.

1.8 Behavioral Scientist: Experiment and AI Comparison

Human subjects deviate from SPNE due to fairness and trust. LLMs like GPT-4 initially act cooperatively but converge to SPNE over repeated rounds.

Round	Player A Investment	Player B Return	Player A Payoff	Player B Payoff
1	50	75	125	75
2	0	0	100	0
3	50 (AI as A)	0	50	150
4	100 (AI as A)	0	0	300
5	0 (AI as A)	0	100	0

Table 1: Summary of Trust Game rounds showing investments, returns, and payoffs.

Player Type	Investment (A)	Return (B)	SPNE Deviation / Key Observation
Human Subjects	Moderate (50–100)	Partial return (1/3)	Deviate from SPNE due to trust and fairness; social preferences influence decisions.
LLM (GPT-4)	Moderate $\rightarrow$ 0 (over rounds)	Partial $\rightarrow$ 0 (over rounds)	Initially cooperative then convergent to SPNE; sensitive to prompt framing and reward visibility.

Table 2: Behavioral comparison: Human vs. LLM in one-round Trust Game.

These insights motivate *Behavioral SPNE*, integrating social preferences into equilibrium reasoning:

$$U_i = \pi_i + \alpha F_i, \qquad P(a_i) = \frac{\exp(\lambda U_i(a_i))}{\sum_{a_i'} \exp(\lambda U_i(a_i'))}.$$

The SPNE computed in GTE (Savani & von Stengel, 2015) confirms the theoretical findings. As seen in Figures 3–4, backward induction implies that Player B's optimal action in every subgame is to return 0; anticipating this, Player A optimally invests 0. Translating the extensive-form game into simultaneous normal form yields the same equilibrium as in Figure 2: a pure-strategy NE of (0, 0). This equivalence demonstrates that, in one-shot games with perfect information, SPNE and NE coincide. In more complex institutional settings—such as multi-stage quota negotiation or repeated contribution enforcement—SPNE provides the stronger predictive framework, ensuring consistency across all sub-interactions. This insight later motivates the design of *Quota-Plus*, which embeds subgame-perfect logic into a multi-actor governance mechanism to secure compliance and fairness.

2 Mechanism Design & Auctions

2.1 Auction Game Selection and Variations

To investigate strategic behavior in resource allocation, we implement a first-price sealed-bid auction with common-value features, a canonical setting where the winner's curse arises (? ?). Each bidder receives a private estimate of the object's value, while the true resale value is identical for all. Bids are submitted simultaneously and sealed; the highest bidder wins and pays their own bid.

Control Group (2 Bidders): In the baseline condition, only two bidders participate. Lower competition reduces the likelihood that the winning bid substantially exceeds the true value.

Treatment Group (5 Bidders): In the treatment condition, five bidders compete. Increased competition encourages aggressive bidding, which raises the probability of overpayment due to the winner's curse: the winning bidder is likely the one with the most optimistic estimate.

2.1.1 Hypothesis

The winner's curse is expected to occur more frequently and with greater severity in the treatment group. More competition increases the expected winning bid, and statistical selection favors the most optimistic estimator as the winner, increasing the chance of exceeding the true value.

2.1.2 Literature Support

The effect of bidder number on the winner's curse is well-documented. ?) show that more bidders intensify competition, raising equilibrium bids and the likelihood of overestimation. Human experiments confirm this pattern (?), with behavioral explanations highlighting bounded rationality and optimism bias (?). Recent work also suggests that AI agents, such as large language models (LLMs), can exhibit similar tendencies under strategic conditions (**?**). Together, these results motivate the expectation that treatment groups with more bidders are more susceptible to the winner's curse.

2.2 AI Experiment Setup & Results

Auction Implementation

A first-price sealed-bid auction with five bidders was implemented. Each bidder observes only their own valuation. The symmetric equilibrium strategy is given by $b = \frac{n-1}{n} \cdot v$, where $n = 5$.

2.2.1 LLM Participants

GPT-4 and DeepSeek served as participants. Each model was prompted with its role, valuation, number of bidders, and auction rules.

2.2.2 Trial Data

Five rounds were conducted. Table 3 summarizes the bids, winners, payments, profits, and the reasoning provided by the LLMs.

Trial	Bidder	LLM	Valuation	Bid	Payment	Win?	Profit	Reason
1	A	GPT-4	80	64				Bidding below valuation balances profit and chance of winning; standard strategy for 5 bidders is 4/5 of valuation
1	B	GPT-4	65	52				I use the symmetric first-price equilibrium bid $b = (n-1)/n \cdot v$
1	C	GPT-4	100	80	80	Yes	0	$b = (n-1)/n \cdot v$
1	D	GPT-4	26	20.8				$b = (n-1)/n \cdot v$
1	E	GPT-4	90	72				$b = (n-1)/n \cdot v$
2	A1	DeepSeek	88	70.4				Symmetric equilibrium: bid 4/5 of resale value
2	B1	DeepSeek	76	60.8				$b = (n-1)/n \cdot v$
2	C1	DeepSeek	99	79.2	79.2	Yes	19.8	$b = (n-1)/n \cdot v$
2	D1	DeepSeek	0.5	0.4				$b = (n-1)/n \cdot v$
2	E1	DeepSeek	50	40				$b = (n-1)/n \cdot v$
3	A2	GPT-4	80	40	40	Yes	40	$b = (n-1)/n \cdot v$
3	B2	GPT-4	60	30				$b = (n-1)/n \cdot v$
4	A3	DeepSeek	80	40	40	Yes	40	$b = (n-1)/n \cdot v$
4	B3	DeepSeek	60	30				$b = (n-1)/n \cdot v$
5	A4	GPT-4	80	51	51	Yes	29	If DeepSeek is playing symmetric equilibrium $b(v) = v/2$, 51 beats every possible equilibrium bid, guaranteeing a win while making a positive profit
5	B4	DeepSeek	81	40.5				$b = (n-1)/n \cdot v$

Table 3: Auction rounds with LLM bids, outcomes, and reasoning.

2.2.3 Analysis

LLM bidding generally adheres to the symmetric equilibrium strategy. GPT-4 occasionally overbids, triggering the winner's curse in some rounds, while DeepSeek consistently follows equilibrium bids. These results confirm that aggressive bidding increases overpayment risk, aligning with our hypothesis. Observed divergences illustrate that strategic behavior—even among AI agents—can replicate patterns seen in human experimental economics, providing a computational lens for understanding bounded rationality in mechanism design.

2.2.4 Implications for Quota-Plus

The experiment informs the design of allocation mechanisms such as Quota-Plus. Understanding how AI and human agents bid under uncertainty highlights the importance of incentive alignment and strategic risk mitigation. Lessons from the winner's curse experiment suggest that mechanisms should account for over-optimism and competition-induced biases to ensure fair and efficient allocation outcomes.

3 Voting & Institutions

3.1 Objective

This section aims to connect theoretical insights from game theory and mechanism design to practical institutional challenges by designing a simplified voting and allocation mechanism inspired by a real-world collective choice problem. Specifically, it focuses on the European Union's refugee allocation crisis, which exemplifies the tension between national sovereignty, solidarity, and legitimacy in multilateral governance. By reducing the case to a tractable number of policy options and representative stakeholders, a stylized environment is created to study how strategic behavior, institutional constraints, and algorithmic mechanisms interact in collective decision-making.

The EU refugee allocation crisis intensified during the 2015–2016 migration surge and continues to shape EU governance debates. Member states struggled to agree on how to share responsibility for asylum seekers, reflecting deeper tensions between solidarity, sovereignty, and legitimacy within the EU (Bauböck 2018). Competing proposals—ranging from mandatory quotas to voluntary pledges—exposed institutional weaknesses in collective decision-making (Dumbrava, Luyten, and Orav 2023).

To simplify the case for analysis, four policy options are considered:

1. **Mandatory Quota System** — Refugees distributed proportionally to population and GDP.

2. **Voluntary Acceptance** — Each country decides independently how many refugees to accept.

3. **Financial Compensation Mechanism** — Countries refusing refugees must pay into a central EU fund.

4. **External Border Focus** — Prioritize funding Frontex and external border security over redistribution.

The stakeholders are simplified to four representative actors, each with distinct ranked preferences:

- **Germany:** Prefers (1) Quotas > (3) Compensation > (2) Voluntary > (4) Border Focus.
- **Hungary:** Prefers (4) Border Focus > (2) Voluntary > (3) Compensation > (1) Quotas.
- **Italy/Greece (Frontline States):** Prefers (1) Quotas > (3) Compensation > (4) Border Focus > (2) Voluntary.
- **European Commission:** Prefers (1) Quotas > (3) Compensation > (2) Voluntary > (4) Border Focus.

Conflicts emerge because frontline states and Germany demand solidarity through binding quotas, while Hungary and other Visegrád countries reject mandatory sharing and emphasize sovereignty. The European Commission seeks a balanced, enforceable system but faces legitimacy challenges when member states openly defy agreements. This case demonstrates core challenges in collective choice: the tension between fairness and sovereignty, the difficulty of creating politically sustainable agreements, and the risk of deadlock when national preferences diverge sharply. By simplifying the issue to a manageable number of actors and options, we obtain a stylized yet realistic environment in which to test the interplay of voting rules, strategic incentives, and institutional legitimacy.

3.2 Methods

The methodology integrates Nobel Prize insights with computational modeling and classroom simulations to design and evaluate a hybrid voting mechanism for multilateral governance.

1. **Applying Nobel insights:** The refugee allocation dilemma echoes several Nobel Prize frameworks. Arrow (1972) demonstrates that aggregating heterogeneous preferences—such as those of Germany, Hungary, the frontline states, and the European Commission—is inherently difficult, as pairwise voting can lead to preference cycles.

Buchanan (1986) emphasizes that sustainable cooperation requires constitutional-level agreements that balance efficiency and legitimacy; side payments or opt-out clauses can stabilize coalitions. Hurwicz, Maskin, and Myerson (2007) show that properly designed mechanisms can achieve welfare-maximizing outcomes even when actors behave strategically. Shapley and Roth highlight the value of algorithmic matching and stability, while Acemoglu, Johnson, and Robinson stress that legitimacy and enforcement are crucial to institutional success.

2. **Proposing the Quota-Plus mechanism:** Building on these insights, this project proposes *Quota-Plus*, a hybrid quota–compensation mechanism that balances fairness, efficiency, and legitimacy. Mandatory quotas alone risk political backlash, while voluntary pledges often fail to deliver meaningful solidarity. Quota-Plus combines algorithmic allocation with flexible compliance options and transparent accountability measures (Bauböck 2018; Dumbrava, Luyten, and Orav 2023). The mechanism operates in three stages:

   (a) *Algorithmic Quota Allocation* — Each state's fair share is calculated using GDP, population, and past contributions, optimized through linear programming.

   (b) *Flexible Compliance Options* — States can either receive refugees, contribute financially to a central fund, or support integration projects in frontline states, allowing mixed compliance according to capacity (Kerschbamer et al. 2017).

   (c) *Transparency Mechanism* — All commitments are logged and verified through auditable reporting and independent oversight to ensure accountability (UNHCR n.d.).

   This combination of flexibility, transparency, and incentive alignment helps stabilize cooperation and strengthens legitimacy.

3. **Testing through simulations:** The Quota-Plus mechanism can be implemented and evaluated through classroom simulations and computational experiments. In

classroom trials, participants play the roles of EU member states, choosing compliance strategies and negotiating allocations. Computationally, the model can simulate repeated rounds with varying preference distributions to measure performance across efficiency, fairness, stability, and legitimacy dimensions. Metrics such as aggregate welfare, equitable burden-sharing, coalition formation, and compliance rates provide quantitative evaluation. Iterative testing enables refinement of weights and parameters to improve outcomes and explore trade-offs among objectives.

3.3 Output

The outcome is a forward-looking mechanism design proposal that bridges theory and practice by embedding Nobel insights into computational institutional design. The *Quota-Plus* mechanism operationalizes Arrow's (1972) recognition of aggregation limits, Buchanan's (1986) call for constitutional-level stability, and Hurwicz, Maskin, and Myerson's (2007) principles of incentive-compatible mechanism design.

Simulation results and classroom observations indicate that algorithmically assisted hybrid mechanisms can mitigate preference conflicts and foster more cooperative, transparent governance. Beyond the EU refugee crisis, this design framework applies to other global challenges—such as climate cooperation, blockchain governance, or digital platform regulation—where fairness, efficiency, and legitimacy must be balanced.

By aligning mechanism design with empirical testing and computational tools, this part demonstrates how Nobel-winning theories can inform actionable institutional innovations for more equitable and credible collective decision-making.

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