





# Discrimination between Social Groups: The Influence of Inclusiveness-Enhancing Mechanisms on Trade

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**Abstract:** The bargaining power of prosumers in a market can vary significantly. Participants can range from industrial participants to powerful and less powerful citizens. Existing trade mechanisms in such markets, e.g., in rural India's energy trade market, show occurrences of discrimination, exclusion, and unfairness. We study how discrimination affects market access, efficiency, and demand satisfaction for the discriminating and discriminated groups via an agent-based simulation, incorporating the available real data. We introduce a mechanism for such markets that is designed for the values of inclusion and equal opportunities. The crux of our mechanism is that goods are divided into smaller units, as determined by the market participants' surplus and demands, and traded anonymously via agents representing the prosumers. We evaluate six hypotheses in a case study about energy trade in rural India, where members of a caste known as Dalits are discriminated by Others. We show that anonymization contributes to the value of inclusion, and the combination of anonymization and inclusion contributes to equal opportunities with respect to market access for both Dalits and Others.

## 1 INTRODUCTION

The possibility of tracing goods to their production and delivery is important for accountability. However, knowing the origin of goods or of payments can enable social discrimination based on, e.g., ethnicity, gender, or caste. The shorter the link between buyers and sellers, the more poignant the opportunity for discrimination. In physical markets, the link is direct as personal contact is required for transactions.


Energy trading in rural India is a clear setting to study discrimination in a physical market. Large parts of rural India lack an infrastructure for automated energy distribution. Solar panels can be a solution for generating energy locally but require a local market for distributing surplus energy. The local market is currently realized by trading batteries. This exchange requires personal contact, implying that the origin of energy can be established. Therefore, this trade cre-


ates an opportunity for social discrimination.


A specific type of discrimination present in the Indian markets is the discrimination between members of higher castes and Dalits (historically, the lowest caste in India). Specifically, individuals of a high caste may not buy energy produced by Dalits since the former may consider the energy produced by Dalits as “impure.” The high caste individuals may not discriminate when selling the energy to the Dalits.


Ideally, increasing personal distance by mediation should reduce the opportunity (not the cause) for discrimination. However, if the mediator is a Dalit, the market is prone to the same discrimination as when the producer is a Dalit. In contrast, if the mediator is of a high caste, discrimination can still happen. The mediator, to maintain reputation or to simply follow the social rules, may block trade across caste lines, practically creating two separate markets.

Considering the factors above, we propose mediation through a local grid as a technological alternative. We compare different market mechanisms with respect to their discriminatory potential and study the effect of these mechanisms on the market performance. In particular, we study the effect of dis-

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crimination on the volumes of trade between people from different caste groups and market efficiency in order to answer the following research question: *Can we reduce the effect of discrimination on market efficiency and trade volumes between (caste) groups by anonymizing trade via agent-based mediation?*

Answering this question is nontrivial. First, a variety of factors, including the distribution of individuals across social groups in a population, their production and consumption characteristics, the market type, and the trade mechanisms supported by it, influence the market outcome. Thus, the influence of discrimination and the mechanisms to reduce the influence must be studied in complex setting, including the additional factors that influence outcomes. Second, introducing and studying such mechanisms in the wild, in a real energy market, is not feasible.

We seek to answer the research question above via a rigorous agent-based market simulation. We compare market access of the different groups, trade volumes between groups, and overall market efficiency in mediated and non-mediated markets. To gain further insights on the effects of discrimination, we simulate different trading protocols considering transaction size and trading rounds. Our simulations are based on the available data about the size and income of different social groups in rural India, and on their energy production and consumption characteristics.

Our contribution in this paper is three fold.

1. We describe a formal model to capture the influence of discrimination on market measures.
2. We develop the first agent-based model (to the best of our knowledge), simulating caste-based discrimination in an energy market.
3. We propose and evaluate two simple yet effective mechanisms (bid splitting and multibidding) to reduce the influence of discrimination.

The rest of the paper is organized as follows. Section 2 describes related works. Section 3 describes the formal model we develop to study discrimination in a market. Section 4 describes the mechanisms we introduce to reduce discrimination, and the the simulation model we develop to study the influence of the proposed mechanisms. Section 5 describes our hypotheses and the experiments we conduct. Section 6 discusses the results of our experiments. Section 7 concludes the paper, highlighting key findings.

## 2 RELATED WORK

We provide a background decentralized electrification in India, and review works on agent-based energy trade and caste-based discrimination in India.

### 2.1 Decentralized Electrification

In a country like India, connecting everyone to a centralized power grid is problematic due to rough terrains and patchy rural settlements (Census of India, 2011), and high costs for distribution companies. As of August 2019, 25 million Indian households still do not have electricity (REC Limited, 2019).

Decentralized solutions such as solar home systems (SHS)—rooftops with integrated solar Photovoltaic (PV) panels—and PV microgrids (capable of supplying electricity to a village for domestic use) are preferable (Bhattacharyya, 2006; Chaurey and Kandpal, 2010; Cust et al., 2007). However, long-term electrification projects are susceptible to many socio-cultural, economic, and technical factors (Urme and Md, 2016; Singh et al., 2017; Trotter, 2016). For example, the choice of target users, and the identification, appointment of a trusted local leader, and community participation is important.

### 2.2 Agent-Based Electricity Trade

As Kirman (1989) argued in his seminal paper, one should study not only market equilibria, but also consider the individual behavior of the traders. For this purpose, a whole research line in agent-based economics has been developed. Our work can be related to the work about choice functions (Nadal et al., 1998), specifically, what is the influence of an agent’s knowledge about the caste system and the status of its trade partners on the agent’s choice function?

The literature on agent-based electricity trade discusses agents that optimize their own utility, e.g., maximizing profits, or maximize utility of the market consumers needs (Bower and Bunn, 1999; Ilic et al., 2012; Sha and Catalão, 2015; Tushar et al., 2014). Li et al. (2011) and Weidlich and Veit (2008) discuss bidding strategy models, indicating that new optimization functions should be developed to take into account the increased uncertainty of energy generation and demands of the renewable energy markets.

Concepts used in bidding and acceptance strategies include memory and trust (i.e., number of times the buyer and seller meet in the market). In this process of exchange, agents also learn about the other agents and change their behavior via different methods, e.g., comparing their own profits with others (Chen, 2012; Winker and Gilli, 2001). Most of the price matching is done via a passive role of buyer in the market where seller decides a price (Lee et al., 2015). Other methods discussed to deal with uncertainty in the market and bidding strategies, are e.g., (Bower and Bunn, 1999; Sha and Catalão, 2015). Fi-

nally, simulation settings for experimental research are discussed in (Ilic et al., 2012; Saad et al., 2011), where different evaluation measures, e.g., social welfare and efficiency of the energy exchange are studied.

The works above cover different aspects of agent-based modeling in energy trade. However, none of those are used to study the effects of discrimination, as we do, in the context of peer-to-peer energy trade.

### 2.3 Caste-Based Discrimination

There is ample evidence for caste-based discrimination in India in almost all sectors (Thorat and Neuman, 2012). Betancourt and Gleason (2000) find that a higher proportion of individuals of Scheduled Castes (and Muslims) in the rural areas of a district leads to a lowering of the provision of medical and educational services to that district, and observe this across all states, providing a direct evidence for discrimination. Borooah et al. (2014) observe that a household's position in the distributional ladder and its chances of being poor are largely dependent on its caste. They find that, even when two households have comparable assets, the household of lower caste gets rewarded lower than the higher caste household. For example, buffaloes in a Scheduled Caste household did not earn (via sale of milk) as much as they did in a higher caste household for "untouchability" reasons.

The role of caste in energy exchange is largely unexplored. Singh et al. (2017) show that castes and sections of the community which did not trust each other for historical reasons were not ready to share energy with each other. In an empirical field study by Shinde (2017), experts from nine different India-based projects confirm the existence of caste-based discrimination in energy sharing. In particular, even though caste-based discrimination is illegal, people belonging to higher castes still discriminate Dalits and refuse to buy from Dalits, affecting the trade volume of batteries between Dalits and Others.

To the best of our knowledge, neither caste-based discrimination nor the influence of discrimination on trade in a market have been studied via simulation models in the current literature. However, other forms of discrimination have been studied. For instance, Bullinaria (2018) studies gender-based discrimination in the setting of career progressions. Takács and Squazzoni (2015) study how inequality can emerge in an idealized labor market (without a history of discrimination) due to information asymmetry. Plous (2003) explains that the stereotypes about low-status groups, e.g., labelling them as 'lazy', lead to their discriminatory treatment in a social context.

## 3 FORMAL MODEL

A population of prosumers is trading energy at a market. We define  $\mathcal{G}$  as the set of all groups. The population is divided into two subgroups:  $\mathcal{D} \in \mathcal{G}$  are the discriminated group and  $\mathcal{O} \in \mathcal{G}$  are the others.

At each time step, each agent  $j$  in the population obtains a production value  $p_j$  and a consumption value  $c_j$  (the energy needs). At first, an agent uses its production to satisfy its needs and then turns to the market to deal with the surplus. We define the surplus  $s_j = p_j - c_j$ . A positive surplus means that the agent has extra production to sell; a negative surplus means that the agent has unmet consumption to satisfy. We subdivide the groups depending on the surplus as follows. For any group  $g \in \mathcal{G}$ :  $g^+ = \{i \in g : s_i > 0\}$ ,  $g^- = \{i \in g : s_i < 0\}$ . We then define the total surplus  $S_g$  and the total demand  $C_g$  of a group  $g$  as:

$$S_g = \sum_{i \in g^+} s_i \text{ and } C_g = \sum_{i \in g^-} s_i$$

Trade in the market moves a resource from an agent with a surplus to an agent with a demand. In the following, for any two groups  $g, g' \in \mathcal{G}$ ,  $T_g^{g'}$  denotes the total trade from members of group  $g$  to members of group  $g'$ . The total of all transactions is defined by totalling the trade in all directions:

$$\tau = \sum_{g, g' \in \mathcal{G}} T_g^{g'}$$

In particular, for only two groups ( $\mathcal{D}$  and  $\mathcal{O}$ ),  $\tau$  is defined as  $\tau = T_D^D + T_D^O + T_O^D + T_O^O$  as Figure 1 shows.

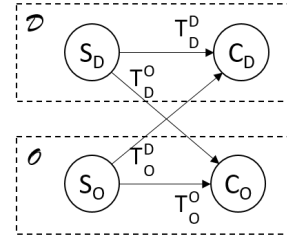


Figure 1: Trade directions between groups  $\mathcal{D}$  and  $\mathcal{O}$ .

For the evaluation of the market and its protocols, we introduce measures about demand satisfaction, selling success, and market efficiency.

Demand satisfaction factors are determined as incoming trade over demand per group:

$$\eta_D = \frac{T_D^D + T_O^D}{C_D} \text{ and } \eta_O = \frac{T_D^O + T_O^O}{C_O}$$

Selling success factors are determined as incoming trade over surplus per group:

$$\theta_D = \frac{T_D^D + T_O^D}{S_D} \text{ and } \theta_O = \frac{T_D^O + T_O^O}{S_O}$$

Two groups,  $g$  and  $g' \in \mathcal{G}$ , are said to have equal opportunity in the market if:

$$|\eta_g - \eta_{g'}| \leq \rho_1 \text{ and } |\theta_g - \theta_{g'}| \leq \rho_2,$$

where  $\rho_1$  and  $\rho_2$  are significance margins. In contrast, the market favors a group  $g$  over group  $g'$ , if:

$$\eta_g - \eta_{g'} > \rho_1 \text{ or } \theta_g - \theta_{g'} > \rho_2.$$

The total amount of trade possible is limited by the total surplus (it is not possible to trade more energy than what is produced) and by the total demand (it does not make sense to trade more energy than what is asked for). Hence, the total trade possible is:

$$\sigma = \min\{C_D + C_O, S_D + S_O\}$$

Market efficiency is defined as total trade over total possible trade:

$$\gamma = \frac{\tau}{\sigma}$$

Thus,  $\gamma = 1$  indicates total market efficiency, but  $\gamma < 1$  indicates a market in which more demand could have been satisfied and surplus production is unnecessarily wasted. The avoidable waste factor of surplus production  $\omega$  is defined as:

$$\omega = 1 - \gamma$$

Similarly, the proportion of unmet demands that a group  $g \in \mathcal{G}$  suffers is defined as  $\delta_g = 1 - \eta_g$ .

**Discrimination.** When considering discrimination in two groups, the effect of discrimination on trade volumes, in terms of the model, can be described as the proportions of trade over the trade directions between and within the two groups as shown in Figure 2.

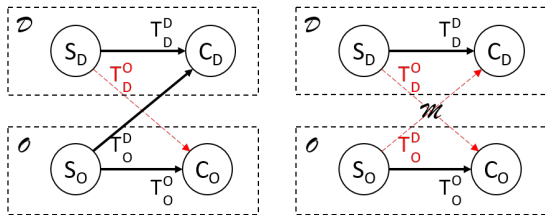


Figure 2: Left: discrimination on trade from  $\mathcal{D}$  to  $\mathcal{O}$ . Right: market segregation due to the discriminating mediator ( $m$ ).

## 4 SIMULATION MODEL

Our description follows the ODD (Overview, Design concepts, Details) protocol (Grimm et al., 2010).

### 4.1 Purpose

Our model simulates trade in a prosumer market, in presence of social discrimination, to understand the effect of discrimination on the market and to evaluate a mechanism for reducing discrimination.

### 4.2 Entities, State Variables, and Scales

**The agents** in our model are the energy prosumers, characterized by the following state variables:

- population to which the agent belongs;
- caste (Dalits or Others);
- (per capita) income; and
- consumption and production values.

**The environment** is the market, characterized by the following state variables:

- market type (bilateral or mediated);
- transaction type (full surplus, bid splitting, or multibidding);

**The collectives** of interest are the agents corresponding to Dalits ( $\mathcal{D}$ ) and Others ( $\mathcal{O}$ ). The following state variable is defined at the level of the collectives:

- discrimination, which specifies the extent to which an agent discriminates trade from another agent.

### 4.3 Process Overview and Scheduling

**The main process** is a SCHEDULER, which executes one of the following trade protocols, depending on the transaction type: (1) FULL\_SURPLUS\_PROTOCOL(), (2) BID\_SPLITTING\_PROTOCOL(), and (3) MULTIBIDDING\_PROTOCOL(). Depending on the protocol, one or more of the following functions are involved.

- TRADE() executes trades between pairs of agents;
- SPLIT\_BIDS() splits bids;
- SELECT\_PARTNERS() selects trade partners;
- DISCRIMINATES() determines whether and agent discriminates trade from another agent; and
- MEASUREMENTS() computes response variables.

One complete run of the model simulates trade among agents in a population for one day. For each run, once the agents and the environment are configured, the SCHEDULER, executes one of the trading protocols and logs the measurements.

### 4.4 Design Concepts

#### 4.4.1 Basic Principles

Our simulation depends on market type and transaction type, which determine how trade happens.

**Market type** In a bilateral market, the agents directly trade energy with each other. In a mediated market, the agents trade energy via a mediator.

In a physical market, bilateral trade means that the prosumers exchange batteries with each other, whereas mediated trade means that a mediator collects and redistributes the batteries. In an online market, e.g., realized on a smart grid, the grid, acting as a mediator, collects and distributes energy.

#### Transaction type

- **Full surplus:** An agent sells its full daily surplus in one transaction. This setting is intended to capture how agents trade batteries in a physical market, where they buy or sell whole batteries (which cannot be divided). For simplicity, we assume that each seller has all of its surplus in one battery. Thus, each trade (buy or sell) involves one battery.
- **Bid splitting** models the exchange of energy, where each production and consumption is divided into chunks of a maximum size. For example, given a maximum chunk size of 1, a production of 2.13 is divided in chunks of sizes 1, 1 and 0.13. Then, each chunk can, in principle, be sold to a partner with the matching demand, but the remaining production or consumption stays with the agent. For instance, in the example above, if the agent sells two chunks of size 1, the production of 0.13 remains with it. The maximum chunk size plays a role in making the system more or less efficient. We choose the smallest surplus or demand value across all agents as the maximum chunk size.
- **Multibidding** models multiple rounds of bidding in which the remaining production from one round can be allocated in the next round to individuals that still have unsatisfied consumption. In each round, bid splitting takes place, considering the smallest surplus or demand value in that round as the maximum chunk size. Multibidding maximizes trade efficiency as trading ends when one of production or consumption is fully satisfied.

#### 4.4.2 Emergence

The market outcomes directly depend on the trades that take place. The trades, in turn, depend on the discriminating behavior of the agents. It is important to note that the effect of discrimination on multiple market variables cannot be determined directly. Several factors, including the distribution of discriminating agents, consumption and production characteristics, and trading protocols influence the effect of discrimination on the response variables. Our simulation seeks to systematically quantify these effects.

#### 4.4.3 Objectives

On the one hand, each agent's objective is to maximize trade (sell all surplus or buy for all demand). On the other hand, some agents may be discriminating (e.g., to conform to social rules) and thus participate in some trades but not others.

#### 4.4.4 Interaction

A pair of agents (a seller and a buyer) interact when they trade energy. Depending on the protocol, (1) an agent can participate in multiple trades and (2) the same pair of agents may trade with each other multiple times, within a trading day.

#### 4.4.5 Stochasticity

- **Income** is computed stochastically. The income range is determined according to income distribution in real data but, within the range, an income value is randomly selected.
- **Production** is computed deterministically from income. Since income is stochastic and production depends on income, production is also stochastic.
- **Consumption** is computed, considering the agent's income as well as the uncertainty about the future energy demand. Thus, consumption is stochastic.
- **Discrimination** behavior is stochastic. A fraction of agents in the population are treated as discriminating. A discriminating agent has a certain probability of successfully trading with an agent it discriminates. This behavior is realistic since an agent may not be discriminating all the times.

#### 4.4.6 Observations

We employ the measures of market efficiency ( $\gamma$ ), the demand satisfaction for the two groups ( $\eta_D$  and  $\eta_O$ ), and the selling success of the two groups ( $\theta_D$  and  $\theta_O$ ).

### 4.5 Input Data

The population, income, and consumption are based on external datasets summarized below.

**Population** We model agent populations after people in eight Indian villages, spanning four states: Andhra Pradesh (AP), Uttar Pradesh (UP), Maharashtra (MH), and Rajasthan (RJ). We select these villages because the Project on Agrarian Relations in India (PARI), a project that studies economies of different regions in India, surveyed households in these villages during 2005–2007, providing important data for our simulation (Rawal and Swaminathan, 2011)

shown in Table 1. Two key pieces of information we exploit from this data are the number households and the percentage of Dalits households for each village.

Table 1: The household composition (of Dalits and Others) and the mean household income (INR per year) of the eight Indian villages (Rawal and Swaminathan, 2011) on which we base our simulations.

Village	Households		Mean Income	
	Total	% $\mathcal{D}$	$\mathcal{D}$	$\mathcal{O}$
Ananthavaram	667	42.4	30,690	93,727
Bukkacherla	292	19.8	19,829	40,596
Kothapalle	372	43.3	26,197	38,962
Harevli	112	36.6	27,540	118,951
Mahatwar	150	58.8	25,077	53,530
Warwat Khanderao	757	32.6	24,843	68,400
Nimshirgaon	250	10.0	41,647	87,393
25 F Gulabewala	204	60.2	25,111	339,078

**Income** The PARI data (Rawal and Swaminathan, 2011) includes the distributions of incomes per caste for each of the eight villages. Table 2 shows examples of income distributions for three villages.

Table 2: The per capita income distributions of Dalits and Others for three villages. Data for all eight villages is in (Rawal and Swaminathan, 2011).

Income Range (INR per year)	Ananthavaram		Harevli		Nimshirgaon	
	$\mathcal{D}$	$\mathcal{O}$	$\mathcal{D}$	$\mathcal{O}$	$\mathcal{D}$	$\mathcal{O}$
<5,500	39.5	26.3	80.3	7.7	49.4	20.5
5,500–10,000	26.1	14.6	12.5	26.1	27.3	28.2
10,000–20,000	23.6	29.3	7.5	11.6	16.1	31.4
20,000–30,000	10.8	11.8	0	10.1	1.2	12.1
30,000–40,000	0	4.4	0	4.3	5.9	0
40,000–50,000	0	2.2	0	0	0	3.1
>50,000	0	11.5	0	10.1	0	4.7

**Consumption** No datasets, providing consumption distributions along with income or caste information, were available for the Indian market. However, the RECS 2015 report (EIA, 2015) classifies the energy consumption of US households by their annual income as summarized in Table 3. We employ this data for computing consumption values for agents in the Indian market. Since consumption in the US market is much higher compared to that in rural India, we perform appropriate scaling (described in Section 4.6).

Table 3: The income and energy consumption distribution in US households based on the RECS report (EIA, 2015).

Household Income (USD per year)	Consumption per Household member (in million BTU)
< 20,000	25.9
20,000–39,999	29.3
40,000–59,999	29.9
60,000–79,999	29.9
80,000–99,999	31.5
100,000–119,999	30.6
120,000–139,999	33.7
> 140,000	36.8

## 4.6 Initialization

**Population** We simulate trading between agents in eight populations of size  $\in \{122, 160, 204, 250, 292, 372, 667, 757\}$  corresponding of actual village sizes. Within each population, the agents are assigned to Dalits or Others according to the data (Table 1).

**Income** Given an agent’s population and caste, its income range is computed according to the distribution of incomes (Table 2). Then, an income is randomly selected within the computed range.

**Production** Individuals produce energy based on their disposable income since they must be able to afford the equipment. Thus, production is computed from income. According to a survey (ICE 360, 2016), Indian households in the the bottom quantile spend around 20% of their income on other expenses, which we consider as disposable income to pay for electricity production. Given that a device with a production of 0.1kWh costs around 1,600 INR and the lifespan of a solar panel is around 20 years, we assume households invest all disposable income for the following 20 years to buy as many devices as they can afford. Thus, the available production is computed by multiplying the production of a single device by the number of devices that a household can afford, given its disposable income for the following 20 years.

**Consumption** First, we map the income of an agent from the Indian range (0–60,000) in Table 2 to the USA range (0–150,000) in Table 3. Then, we assign an initial consumption value to the agent from Table 3. Next, we scale the initial consumption value based on the average consumption values (in 2015) of Indian household, given as 806 kWh (compared to 12,984 kWh of US) (The World Bank, 2014). Yearly consumption is then converted to daily consumption.

The energy needs of an average Indian household and an average rural Indian household may differ. Thus, the consumption values are further rescaled, controlled by the consumption offset parameter  $\in \{0.25, 0.5, 1.0\}$ . Finally, for each agent, a daily consumption value is sampled from a normal distribution centered on the scaled consumption value for the agent, and having a standard deviation controlled by the consumption std.dev parameter  $\in \{10, 50\}$ .

**Discrimination** In a bilateral market, the parameter fraction of  $O$  discriminating  $\mathcal{D} \in \{0, 0.2, 0.5, 0.8, 1\}$  controls the number of agents in  $O$  that discriminate the agents in  $\mathcal{D}$  (one direction). A discriminating agent in  $O$  refuses to buy from an agent in  $\mathcal{D}$ , if paired so by the protocol, with a high probability (90%).

In a mediated market, the same parameter (fraction of  $O$  discriminating  $\mathcal{D} \in \{0, 0.2, 0.5, 0.8, 1\}$ ) controls the percentage of inter-caste trades (in either direction) that the mediator allows.

## 4.7 Submodels

Listing 1 describes the three protocols introduced in Section 4.4. The full surplus protocol is a baseline, representing how batteries are likely traded in a physical market. The bid splitting and multibidding protocols capture the mechanisms we introduce.

Each protocol starts by sorting the bids. The sorting order makes a difference during partner selection (Listing 2). In the full surplus protocol, both sellers' and buyers' bids are sorted in the descending order. This captures the intuition that a seller wants to sell his or her battery to a buyer with the highest possible demand but less than the seller's surplus. In contrast, the other two protocols sort the sellers' bids in descending order and buyers' bids in ascending order giving priority to sellers with higher surplus and buyers with lower demand. However, since the trade happens with split bids in bid splitting and multibidding protocols, all agents get an opportunity to trade.

The simulation is implemented in Python 3 based on the MESA simulation framework<sup>1</sup> with custom-made agents and actors. The source code is available on GitHub<sup>2</sup>. The simulation was executed on a workstation with 48 cores and 64GB of RAM.

<sup>1</sup><https://github.com/projectmesa/mesa>

<sup>2</sup>[https://github.com/bennati/EnergyVCG/tree/discrimination\\_dev](https://github.com/bennati/EnergyVCG/tree/discrimination_dev)

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### Listing 1 Trading protocols

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```

1: procedure FULL_SURPLUS_PROTOCOL( $S, B$ )
2:   SORT_BIDS( $S, \text{'DSC'}, B, \text{'DSC'}$ )
3:   TRADE( $S, B$ );
4:   return MEASUREMENTS()
5: procedure BID_SPLITTING_PROTOCOL( $S, B$ )
6:   SORT_BIDS( $S, \text{'DSC'}, B, \text{'ASC'}$ )
7:   SPLIT_BIDS( $S, B$ )
8:   TRADE( $S, B$ )
9:   return MEASUREMENTS()
10: procedure MULTIBIDDING_PROTOCOL( $S, B$ )
11:  SORT_BIDS( $S, \text{'DSC'}, B, \text{'ASC'}$ )
12:  while  $\neg(S.BIDS().EMPTY())$ 
13:    do
14:     $\parallel B.BIDS().EMPTY()$ 
15:    SPLIT_BIDS( $S, B$ )
16:    TRADE( $S, B$ )
17:  return MEASUREMENTS()
18: procedure TRADE( $S, B$ )
19:   $partners\_list \leftarrow \emptyset$ 
20:   $next\_partners \leftarrow \text{SELECT\_PARTNERS}(S, B)$ 
21:  while  $next\_partners \neq \emptyset$  do
22:     $partners\_list.ADD(next\_partners)$ 
23:     $next\_partners \leftarrow \text{SELECT\_PARTNERS}(S, B)$ 
24:  for all  $partners \in partners\_list$  do
25:    PERFORM_TRADE( $partners[0], partners[1]$ )
26:  UPDATE_BIDS( $S, B$ )

```

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## 5 EXPERIMENTS

We evaluate the following hypotheses.

- H<sub>1</sub>:** Discrimination prevents Dalits from accessing the market, hence reducing  $\theta_D$ .
- H<sub>2</sub>:** Discrimination reduces market efficiency  $\gamma$ .
- H<sub>3</sub>:** In a mediated market, implemented with a discriminating mediator, the efficiency  $\gamma$  as well as the satisfaction of both Dalits  $\eta_D$  and Others  $\eta_O$ , will be worse than in the non-mediated case.
- H<sub>4</sub>:** The bid-splitting strategy increases the efficiency of trade  $\gamma$  even if discrimination occurs.
- H<sub>5</sub>:** Given H3 and H4, bid splitting increases the range of situations in which a mediated configuration is preferable, for efficiency  $\gamma$  and  $\eta_D$ , over a bilateral configuration.
- H<sub>6</sub>:** In the condition that total surplus is larger than total demand:  $S_D + S_O > C_D + C_O$ , where there is the possibility of satisfying the needs in the market completely, discrimination prevents trade  $T_D^O$ , which might reduce the demand satisfaction  $\eta_O$ .

Simulations were run for 10 trading days, for each combination of population size  $\in \{122, 160, 204, 250, 292, 372, 667, 757\}$ , consumption offset  $\in \{0.25, 0.5, 1.0\}$ , consumption std.dev  $\in \{10, 50\}$ , and fraction of

**Listing 2** Bid splitting and Partner selection

```

1: procedure SPLIT_BIDS( $S, B$ )
2:    $all\_bids \leftarrow S.BIDS() \cup B.BIDS()$ 
3:    $max\_chunk\_size \leftarrow \text{MINIMUM}(all\_bids)$ 
4:   for all  $s \in S$  do
5:      $s.split\_bids \leftarrow \text{SPLIT}(s.bid, max\_chunk\_size)$ 
6:   for all  $b \in B$  do
7:      $b.split\_bids \leftarrow \text{SPLIT}(b.bid, max\_chunk\_size)$ 
8: procedure SELECT_PARTNERS( $S, B$ )
9:   while  $i < S.LENGTH()$  do
10:    while  $j < B.LENGTH()$  do
11:      if  $protocol == \text{'Full\_Surplus'}$  then
12:         $match\_condition \leftarrow S[i].bid \geq B[j].bid$ 
13:      else
14:         $match\_condition \leftarrow$ 
           $S[i].split\_bids[0] == B[j].split\_bids[0]$ 
15:      if  $match\_condition == \text{True}$  then
16:        if  $\text{DISCRIMINATES}(S[i], B[j]) == \text{True}$  then
17:           $i \leftarrow i + 1$   $\triangleright$  Discriminating seller
18:        else if  $\text{DISCRIMINATES}(B[j], S[i]) == \text{True}$ 
          then
19:           $j \leftarrow j + 1$   $\triangleright$  Discriminating buyer
20:        else
21:          return  $\langle i, j \rangle$   $\triangleright$  No discrimination
22:         $j \leftarrow j + 1$ 
23:         $i \leftarrow i + 1$ 
24:   return  $\emptyset$ 

```

$O$  discriminating  $\mathcal{D} \in \{0.0, 0.2, 0.5, 0.8, 1.0\}$ , resulting in 240 samples, with 10 replications each.

First, we analyze the sensitivity of important observable variables (market efficiency  $\gamma$  and market access for Dalits with production surplus  $\theta_D$ ) to variation of the control variables above. In this analysis, a market is assumed with bilateral trade among agents using FULL\_SURPLUS protocol. The sensitivity analysis is used to configure the following experiments.

**Experiment 1** compares the efficiency and satisfaction in bilateral markets, for varying discrimination by agents, in markets with different transaction types ( $H_1$  and  $H_2$ ).

**Experiment 2** compares the efficiency and satisfaction of a bilateral and a mediated configuration, with and without bid splitting, against discrimination ( $H_3$ ,  $H_4$ , and  $H_5$ ).

**Experiment 3** compares the reduction of satisfaction factors by discrimination (in particular, the slope in demand satisfaction) in cases with surplus production with that in cases with shortage, both in bilateral and mediated markets ( $H_6$ ).

Table 4: Regression coefficients from sensitivity analysis.

	Estimate	Std.Error	Pr(>  t )
Coefficients for $\gamma$ :			
(Intercept)	1.272	8.2e-3	<2e-16
Fraction of			
$O$ discriminating $\mathcal{D}$	-0.095	5.1e-3	<2e-16
Consumption offset	-8.024	0.109	<2e-16
Consumption std.dev.	-9.5e-3	2e-4	<2e-16
Population size	-5e-6	8.5e-6	0.559
Consumption offset			
$\times$ std.dev.	0.124	3e-3	<2e-16
Coefficients for $\theta_D$ :			
(Intercept)	0.126	0.01	<2e-16
Fraction of			
$O$ discriminating $\mathcal{D}$	-0.295	6.4e-3	<2e-16
Consumption offset	4.708	0.135	<2e-16
Consumption std.dev.	5e-3	2.5e-4	<2e-16
Population size	-1.7e-5	1.1e-5	0.0992
Consumption offset			
$\times$ std.dev.	-0.014	3.8e-3	0.0002

## 6 Results and Discussion

**Sensitivity Analysis** The average  $\gamma$  and  $\theta_D$  values from 2400 observations were 0.687 and 0.372, respectively. Average within-sample variance resulting from random generation processes in the simulations was 5% and 14% of total variance for  $\gamma$  and  $\theta_D$ , respectively, leaving the rest to be explained from parameter variations. Table 4 shows the results of multiple regression to test sensitivity, with adjusted  $R^2$  values of 0.76 and 0.74, respectively.

Discrimination and consumption distribution have strong and significant effects on the simulation outcomes. Thus, in testing hypotheses, we differentiate the variable analyzed with respect to the values of these two parameters.

Population size has no relevant effect. ANOVA with Tukey test did not reveal significant differences between average outcomes for different population sizes. Since larger population sizes have negligible effects and largely affect simulation time, we perform further experiments on populations of 100 agents.

For hypothesis testing, we formed a dataset, containing results from 10 replications of simulations of 10 trading days. Each replication freshly generated random variables for each of the possible combinations of discrimination (5 values as above), consumption distribution characteristics (6 combinations as above), market type  $\in \{\text{bilateral, mediated}\}$ , and transaction type  $\in \{\text{full daily surplus, bid split, multi-bid}\}$ , resulting in 18000 observations.



## 6.1 H<sub>1</sub> (Market Access)

Figure 3 shows the market access for Dalits, averaged over the transaction types, for the different consumption distributions. In all cases, the effect of discrimination on  $\theta_D$  is significant ( $p < 0.001$ ). Figure 4 shows the market access for Dalits for each transaction type, averaged over different consumption characteristics, for different discrimination levels. Again, the difference, across discrimination levels, was significant ( $p < 0.001$ ). These results confirm that discrimination reduces the market access for Dalits (H<sub>1</sub>).

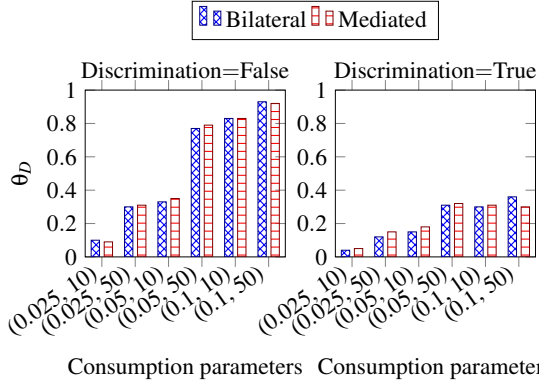


Figure 3: Average  $\theta_D$  values for different consumption distribution parameters (offset, SD) in non-discriminating and discriminating bilateral and mediated trades.

Further, with no discrimination (Figure 3, left), simulated results did not significantly differ between bilateral and mediated trading. However, with discrimination (Figure 3, right), for the right most consumption configuration, the difference in  $\theta_D$  between bilateral and mediated markets was significant, showing that a discriminating mediator, segregating the market, can further influence  $\theta_D$ .

Finally, transaction type had little effect on the market access for Dalits in both bilateral and mediated markets. Figure 4 shows the result for bilateral case (results for the mediated case are similar).

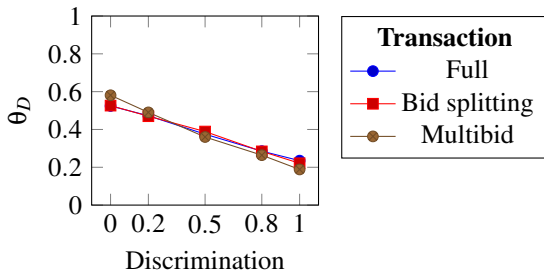


Figure 4: Average effect from fraction of  $O$  discriminating  $D$  on  $\theta_D$ , under different transaction types in bilateral trade.

## 6.2 H<sub>2</sub> (Market Efficiency)

Figure 5 shows the effect of discrimination on market efficiency (averaged across consumption distributions) for different transaction types. The effect of discrimination on market efficiency was significant ( $p < 0.001$ ), confirming H<sub>2</sub>. Further, we observe that the difference in efficiency between transaction types was also significant ( $p < 0.001$ ). These results are for the bilateral market. Similar results are obtained for mediated markets (Section 6.3).

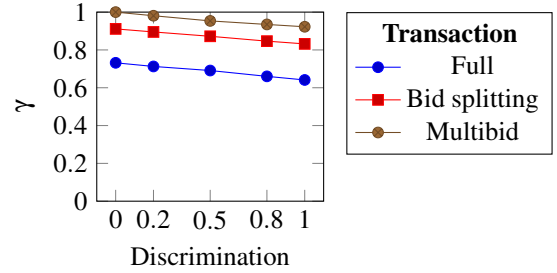


Figure 5: Average effect of discrimination on market efficiency  $\gamma$  under different transaction types in bilateral trade.

## 6.3 H<sub>3</sub> (Discriminating Mediator)

Since a discriminating mediator may separate the markets for Dalits and Others, not all trade opportunities can be utilized, which can potentially lower market efficiency and demand satisfaction (H<sub>3</sub>).

Figure 6 shows the effect of discrimination on efficiency and demand satisfaction in a mediated market. The differences were significant ( $p < 0.001$ ), confirming H<sub>3</sub>. Further, it is interesting to observe that, discrimination reduces the demand satisfaction for not only the Dalits ( $\eta_D$ ) but also the Others ( $\eta_O$ ). However, the margin of difference is much higher for the Dalits than the Others.

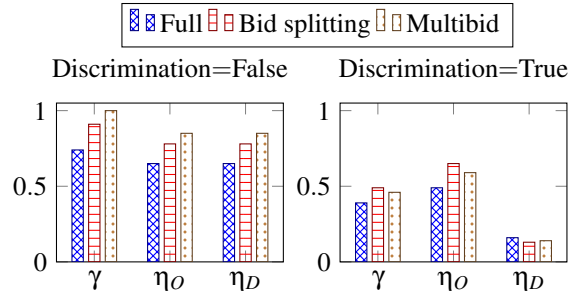


Figure 6: Average values of efficiency ( $\gamma$ ), demand satisfaction of Others ( $\eta_O$ ) and Dalits ( $\eta_D$ ) in a mediated market with a non-discriminating and a discriminating mediator.

## 6.4 H<sub>4</sub> (Bid Splitting)

Bid splitting, i.e., selling the daily surplus in fixed chunks, as well as the multibid market with variable chunks, increases efficiency in bilateral and mediated markets, with and without discrimination, as Figures 5 and 6 show, confirming H<sub>4</sub>.

## 6.5 H<sub>5</sub> (Bid Splitting and Mediation)

Given H<sub>4</sub> results, it is tempting to assume that it would be preferable to implement a mediated system with some bid-splitting mechanism, even if discrimination is possible. However, as Figures 7 and 8 show, this is not the case. That is, if there is discrimination,

- (1) the efficiency (Figure 7) of the mediated market is worse than that of the bilateral market; and
- (2) the demand satisfaction of Dalits (Figures 8) is worse (to a greater degree than efficiency) in the mediated market than in the bilateral market.

Thus, we could not confirm H<sub>5</sub>. In essence, we observe that a discriminating mediator is worse than a bilateral market with discrimination.

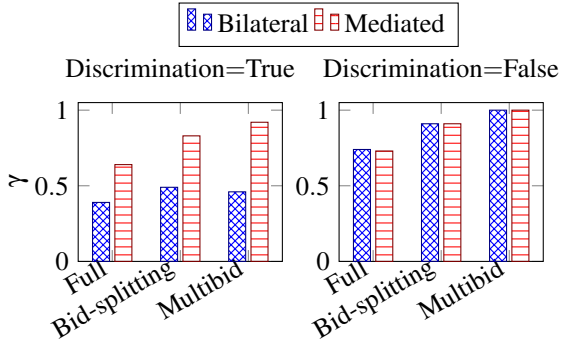


Figure 7: Market efficiency ( $\gamma$ ), without and with discrimination, in mediated and bilateral markets.

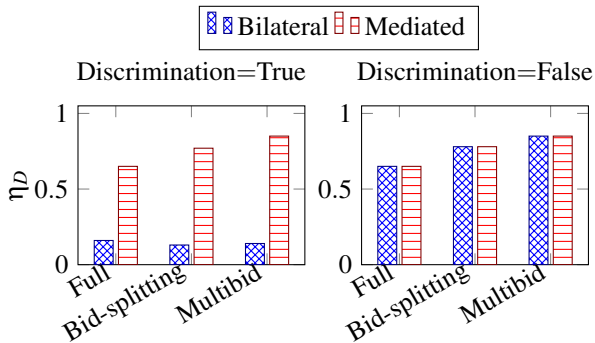


Figure 8: Demand satisfaction for Dalits ( $\eta_D$ ), without and with discrimination, in mediated and bilateral markets.

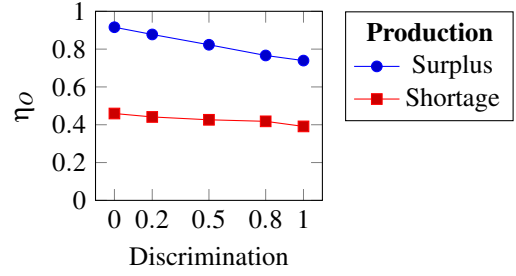


Figure 9: Effect of discrimination on  $\eta_O$  in bilateral trade, in situations of surplus production and shortage.

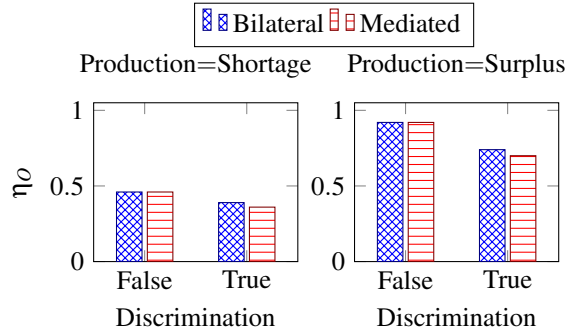


Figure 10: Effect of discrimination on Others' demand satisfaction ( $\eta_O$ ) in bilateral and mediated markets.

## 6.6 H<sub>6</sub> (Demand Satisfaction)

The preceding hypotheses were mainly about the negative effects on Dalits. However, in some cases, discrimination may also affect the discriminating Others.

Complete demand fulfillment is possible if the total surplus production from the entire population exceeds the total demand, with some margin for chunk size  $\epsilon$ , i.e.,  $\eta_O = 1 - \epsilon$ . However, when Others refuse to buy from Dalits, possible fulfillment cannot not be realized in some cases, resulting in a discrimination-induced reduction of  $\eta_O$ . Figures 9 and 10 show this effect. The effect of discrimination on  $\eta_O$  was significant ( $p < 0.001$ ) in both shortage and surplus cases, confirming H<sub>6</sub>. However, we observe that this effect is stronger with a surplus as opposed to shortage.

## 7 Conclusions

**Discrimination has an overall negative effect on market.** Our simulation confirms the negative effect of discrimination in prosumer markets in terms of reduced trade efficiency (H<sub>2</sub>) and, in particular, reduced market access for the discriminated group (H<sub>1</sub>). We show how discrimination can damage the discriminating group as well. By restricting market access of the discriminated group and with it the overall trade vol-

ume, the demand satisfaction of both discriminated and discriminating groups are affected.

**Increasing production may not reduce discrimination.** We show that discrimination prevents complete demand satisfaction even when production is surplus ( $H_6$ ). Thus, subsidies for the purchase of equipment, so as to increase production capacity, especially, that of the discriminated group, would not solve the problem. On the contrary, their positive effect would be eroded by discrimination.

**Mediation with discrimination is worse than bilateral trade.** Some people may have regular overproduction and some regularly suffer from shortage, instigating trading opportunity. As long as no electricity grid is in place, surplus energy will have to be stored in and traded via batteries. On the one hand, bilateral trade, requiring physical contact, is subject to discrimination. On the other hand, mediation increases personal distance and can potentially reduce discrimination. However, we show that, a mediated market with discriminating mediator is worse than a non-mediated market for both Dalits and Others ( $H_3$ ).

**Agent-based mediation reduces discrimination.** A human mediator is subject to the same prejudices as the rest of the society. If the mediator is a Dalit, the Others may not buy from the mediator. If the mediator is an Other, he or she may segregate the market to conform to social rules. We study agent-based mediation, where agents trade on behalf of humans. We argue that agents designed with the values of anonymization and inclusion reduce discrimination. We propose a mechanism, involving bid splitting and multibidding, for agents to trade energy, e.g., in a local grid. Our overall simulation results show that the proposed mechanism is effective in reducing discrimination.

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