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UNIVERSITY OF CALIFORNIA,
IRVINE

Matching Mechanisms for social good: case studies in transport congestion, low-income housing, and food surplus redistribution

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Computer Science

by

Julius Ceasar Aguma

Dissertation Committee:
Professor Amelia Regan and Professor Sandy Irani, Chair
Professor Michael Dillencourt

2022

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DEDICATION

To my 16 year old self, my mums, all siblings and cousins that remind me to keep playing, and all my great friends that make the present a beautiful surreal reality. I love you.

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VITA

Julius Ceasar Aguma

EDUCATION

Doctor of Philosophy in Computer Science **2022**
University of California, Irvine *Irvine, CA*

Master of Science in Computer Science **2020**
University of California, Irvine *Irvine, CA*

Bachelor of Science in Computer Science **2018**
Missouri University of Science and Technology *Rolla, MO*

RESEARCH EXPERIENCE

Graduate Research Assistant **2018–2022**
University of California, Irvine *Irvine, CA*

Undergraduate Research Assistant **2016–2018**
Missouri University of Science and Technology *Rolla, MO*

TEACHING EXPERIENCE

Teaching Assistant **2018–2021**
University of California, Irvine *Irvine, CA*

PUBLICATIONS

- Julius Ceasar Aguma and Michael Demirev. 2022. *Algorithmic Waste Reduction*. In ACM SIGCAS/SIGCHI Conference on Computing and Sustainable Societies (COMPASS) (COMPASS '22). Association for Computing Machinery, New York, NY, USA, 529–544. https://doi.org/10.1145/3530190.3534815 [5].

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ABSTRACT OF THE DISSERTATION

Matching Mechanisms for social good: case studies in transport congestion, low-income housing, and food surplus redistribution

By

Julius Ceasar Aguma

Doctor of Philosophy in Computer Science

University of California, Irvine, 2022

Professor Amelia Regan and Professor Sandy Irani, Chair

For several decades now, matching mechanisms have been deployed, sometimes implicitly, to solve economic and social problems with unprecedented efficiency. Most notably, the kidney transplant matching algorithm has been key in saving many lives, 39,000 donation in 2019 alone[47]. Likewise, the National Residency Matching Program successfully employed in the United States today uses a matching mechanism that places medical students into hospital residencies. A similar mechanism is used in college and public school admissions around the United States, most famously, in the Boston and New York City. This dissertation will continue this long history of applying matching mechanisms towards efficiently solving social problems.

We begin with a summary of relevant definitions and other terminology in chapter 1, all of which will be applied in the chapters that follow. Chapter 2 will examine two concurrent social problems, over-production of resources that contributes to global waste, and lack of access to wasted resources by people living on the economic margin. We will contrast two possible solutions to both problems, that is, a decentralized vs a centralized matching solution. The feasibility of both solutions will be tested through theoretical investigation and two qualitative case studies in food surplus redistribution in the United Kingdom and allocation

of housing to unhoused household in Los Angeles County during the pandemic.

Chapter 3 will give a more detail examination of allocation of housing to the unhoused by examining the efficiency and robustness to manipulation of the algorithm that was employed by LA county vs a centralized matching mechanism. Whereas Chapter 4 will explore an online matching mechanism solution to the problem of traffic congestion pricing. The proposed solution combines a matching algorithm, which assigns drivers to routes at the time of travel, with an anticipatory pricing mechanism that determines how much each travelling driver pays if they choose to use a congested route.

The conclusion will present open problems implied in the preceding three chapters.

Chapter 1

Introduction

1.1 Matching Mechanisms

In the context of this text, a matching mechanism is a model or market where allocations are made based on preferences. In such a mechanism, we are asked to allocate some resource like housing or labour to some kind of demand/ set of consumers. The allocation is typically not driven by prices as it is in a financial demand-supply market but rather preferences. The allocations could be one-to-one, where a single unit of a resource is matched to a single consumer from the set, or many-to-one, where a bundle of resource units is allocated to one consumer or rather a group of consumers have to share one resource. Below we will categorize some of the popular types of matching mechanisms.

1.1.1 Cardinal vs Ordinal

In **ordinal mechanisms**, each consumer reports an ordered preference list over the resources. For example, a list of colleges in the order they are preferred by a student in a college admissions mechanism [49]. A **cardinal mechanism** is one where each consumer has a non-negative utility that they wish to maximizes, for example, buyers in a housing market with prices [64].

1.1.2 Offline vs Online

The setting of a matching mechanism could be **offline**, which means that all the allocations of resources to all the consumers are done all at once then reported to the consumers. For example, college admissions are typically done offline. Whereas **online** matching mechanisms are those where the consumers are revealed to the mechanism one at a time, and the allocation to each consumer is done at the time they are revealed to the mechanism. A good example of online matching mechanisms is google Ad allocation [78].

1.1.3 One-sided vs Two-sided

Another major distinguishing feature is whether one or both sides of a matching mechanism have preferences over the other side. Suitably, if both sides of a matching mechanism have preferences over the other side, we classify this under **two-sided** because a matching should satisfy both sides' preferences. However if only one side has preferences over the other side then we typically classify this as a **one-sided** matching mechanism. A good example of two-sided matching(also called stable matching) is college admission where the student and the college have to choose each other [49], and for one-sided, the allocation of housing to buyers or un-housed persons [64].

1.2 Definitions

As earlier defined, matching mechanism allocate a set of resources to a set of consumers typically on the basis of preference. Below we will define common features of a good matching mechanism that are relevant to the rest of this text.

1.2.1 Pareto Optimality

Pareto Optimality is a measure of the fairness of an allocation. Below is a formal definition.

Given n consumers and n resources, an allocation $X = (x_1, x_2, ..., x_{n-1}, x_n)$, where x_i is the allocation to consumer i, we say X is Pareto optimal if it is not Pareto dominated by any other allocation $X' = (x'_1, x'_2, ..., x'_{n-1}, x'_n)$.

Allocation X' Pareto dominates X if each consumer i is satisfied by their allocation in X either more or equally to if they got X',

$$x_i \succcurlyeq x'_i, \forall i$$

with at least one consumer j for whom the satisfaction in X is strictly better than in X',

$$x_j \succ x'_j, \exists j.$$

[1]

Using utilities, we could also state this as, an allocation X' Pareto dominates X if for each consumer i:

$$U_i(x'_i) \geq U_i(x_i), \forall i$$

with at least one consumer j for whom,

$$U_j(x'_j) > U_j(x_j), \exists j.$$

1.2.2 Strategy Proofness

Strategy proofness (also referred to as incentive compatibility) is the mitigation of possible manipulation in a matching mechanism by the involved agents in attempt to get better allocations. The manipulation is normally possible through false representation of state by an agent. An easy example of manipulation is a consumer misreporting their preferences.

Therefore, a mechanism is strategy proof if truth-telling is a utility maximising strategy[1]. That is, given an agent i whose true preference is x_i, but reports some false preference x'_i; a strategy proof mechanism ensures that,

$$U_i(x_i) \geq U_i(x'_i).$$

If the utility after true representation of self is better or equal to the utility after misrepresentation, then there is no gain to manipulation.

1.2.3 Individual Rationality

For individual rationality, we assume that no one agent in a matching mechanism wants to be worse off than how they came into the allocation. This could manifest itself in a few ways given the setting of the matching.

Individual Rationality with initial endowments

For cardinal utilities, the utilities after allocation can not be non-negative, that is,

$$U_i \geq 0, \forall i.$$

Individual Rationality with initial endowments

Initial endowments exists in mechanisms where the agents come in with an allocation already and are looking for an subjective upgrade. For example, in a housing market, individuals normally have a place of shelter and are looking for an option that is better or at least not worse than their current shelter.

1.2.4 Core

An allocation is in the core of a mechanism if no subset of the agents/consumers can do better outside of the core allocation[107]. That is, let A be the set of n agents in a matching mechanism, and $B \subseteq A$ with m agents, such that $|A| \geq |B|$ or $n \geq m$. We say that an allocation $X = (x_1, x_2, ..., x_{n-1}, x_n)$ is a core allocation if for any size(m) of B, and any other allocation $X' = (x'_1, x'_2, ..., x'_{m-1}, x'_m)$,

$$x_i \succcurlyeq x'_i, \forall i \in B.$$

In other words, no subset of the agents or consumers can do better outside of the core allocation. Note that a core is stronger than, and immediately implies Pareto optimality.

1.2.5 Stability

For most two-sided matching mechanisms, stability of the matching is the first desired quality because of the preferences on both sides. Stability, therefore, is achieved when there exists no blocking pair among all the pairings in a matching[49].

Blocking pair

A blocking pair is a set of two matched pairs where each side of the pairings prefers to be matched to the side in the other pair (figure 1.1). Consider agents, A, B and C, D to be from opposite sides of two-sided-matching. Also consider a matching, μ, where $A - B(A$ is matched to $B)$ and $C - D(C$ is matched to $D)$. But $D \succ_A B(A$ prefers D to $B)$,$B \succ_C D(C$ prefers B to $D)$, $B \succ_B D(C$ prefers B to $D)$, and $A \succ_D C(D$ prefers A to $C)$. Since each agent in their respective pairings prefers the other agent in the same pair, then these two pairs form a blocking pair.

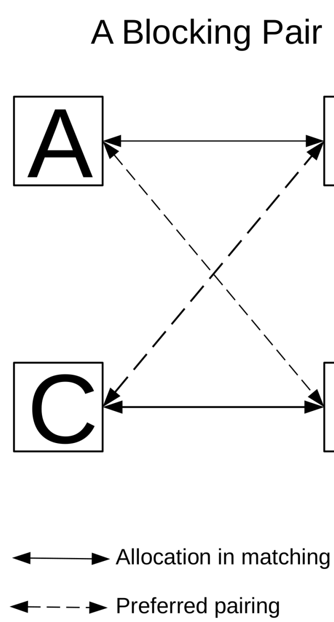


Figure 1.1: A Blocking pair: A is matched to B but prefers D and C is matched to D but prefers B.

1.3 Thesis Overview

The rest of this dissertation will present different applications of matching mechanism to solve a number of social problems. Chapter 2 will contrast two surplus redistribution solutions to this paradox. (1) Local independent donations between producers and donation centers. (2) Redistribution by way of a global redistributor (what we will call a core redistributor) who collects donations from all available producers and redistributes the surplus to all donation centers respective of their demanded quantities. We mathematically show that an optimal allocation of the surplus that minimizes waste and maximizes social welfare is only possible with a core redistributor. As this is a deeply social and economic problem rather than mathematical, we also qualitatively study two cases; (1) food waste and food insecurity in the UK, and (2) Los Angeles County's project RoomKey: a pandemic effort to house covid-vulnerable unhoused persons in vacant hotels and motels. Both case studies give more support for a core redistribution as a solution to waste from overproduction and lack of access to essential resources.

Chapter 3 take a deeper look at project RoomKey, presenting a matching mechanism alternative to assign housing options to the unhoused in a way that maximizes social welfare (Pareto optimality) and minimizes susceptibility to strategic manipulation(strategy-proofness). Additionally, we argue that this automated solution would cut down on the amount of funding and personnel required for the assignment of housing to unhoused persons. This alternative is not suggested as a replacement of current solutions to homeless housing assignments but rather improve upon them.

Chapter 4 details another matching mechanism for assigning drivers to routes where the drivers pay a toll for the marginal delay they impose on other drivers. The simple matching mechanism is derived from the deterministic algorithm for online bipartite matching proposed in [14]. The toll, which is anticipatory in design, is an adaption of one proposed in [34]. We prove that the matching mechanism proposed here is Pareto user-optimal, that is, it is fair to all drivers and achieves a competitive ratio of $1 + log(m)$, where m is the number of available routes, when applied with a goal of minimizing total network travel cost.

Finally, we will conclude with a series of open problems from each of the areas explored in chapters 2,3, and 4.

Chapter 2

Algorithmic Surplus Redistribution[1]

Motivated by a desire for waste reduction through surplus redistribution, we explore the paradox of overproduction of resources that are wasted at several levels of the supply chain and the concurrent lack of access to, in most cases, overproduced basic resources by low income socioeconomic classes to whom resource access is normally only available through donation centers. To that end, we contrast two surplus redistribution solutions in this chapter. (1) Local independent donations between producers and donation centers. (2) a core redistribution. We mathematically show that an optimal allocation of the surplus that minimizes waste and maximizes social welfare is only possible with a core redistributor. We provide further support for core redistribution through two case studies, (1) food waste and food insecurity in the UK, and (2) Los Angeles County's project RoomKey: a pandemic effort to house covid-vulnerable unhoused persons in vacant hotels and motels.

[1]The material in this chapter is from a published work with Demirev[5].

2.1 Introduction

In many resource industries within capitalist economies today, a large amount of surplus is created from overproduction [81, 45, 68, 76, 101]. This surplus contributes to the massive amounts of global waste; with annual estimates of 931 million tonnes of food wasted in 2019 (17% of the global food production) [56], more than 92 million tonnes of textile waste (two thirds of this ends up in landfills) [84, 110],over 50 million tonnes of electronic waste [86, 13], not to mention other resources whose waste is hard to track and quantify. For example, it is not clear how many hotels and motels are wasted annually, or how much clean water and pharmaceutical waste is generated in affluent communities around the world.

In the same capitalist economies, however, the income gap between the poorest and wealthiest grows larger every day [113, 61, 97, 90, 82] (see figure 2.1 for the income gap growth in China, Russia, UK, and USA since 1971). This wide separation of economic classes continues to marginalize low income communities to a reality with limited access to essential resources [35, 69, 27]. This is evident from the gentrification seen in most major cities across the globe [119, 127, 66, 104, 75, 74, 70]. While there is an overproduction of resources, there is a lack of access to those resources by the low income classes that cannot afford the costs [18, 115, 103]. This systemic failure is most evident in times of natural disasters/emergency situations during which the more affluent communities have an over-supply of resources while marginalized communities experience scarcities. A quick example is the response in Puerto Rico after Hurricane Maria compared to Texas and Florida after Hurricane Harvey and Irma [121].

There are many issues that lead to the creation of global waste, most of which arise from consumer behavior at the household level [122, 123]. However, there is still a considerable amount of surplus created within the supply chain that can be redistributed to those that lack access to the surplus resources [122, 123]. This research, therefore, highlights the structural

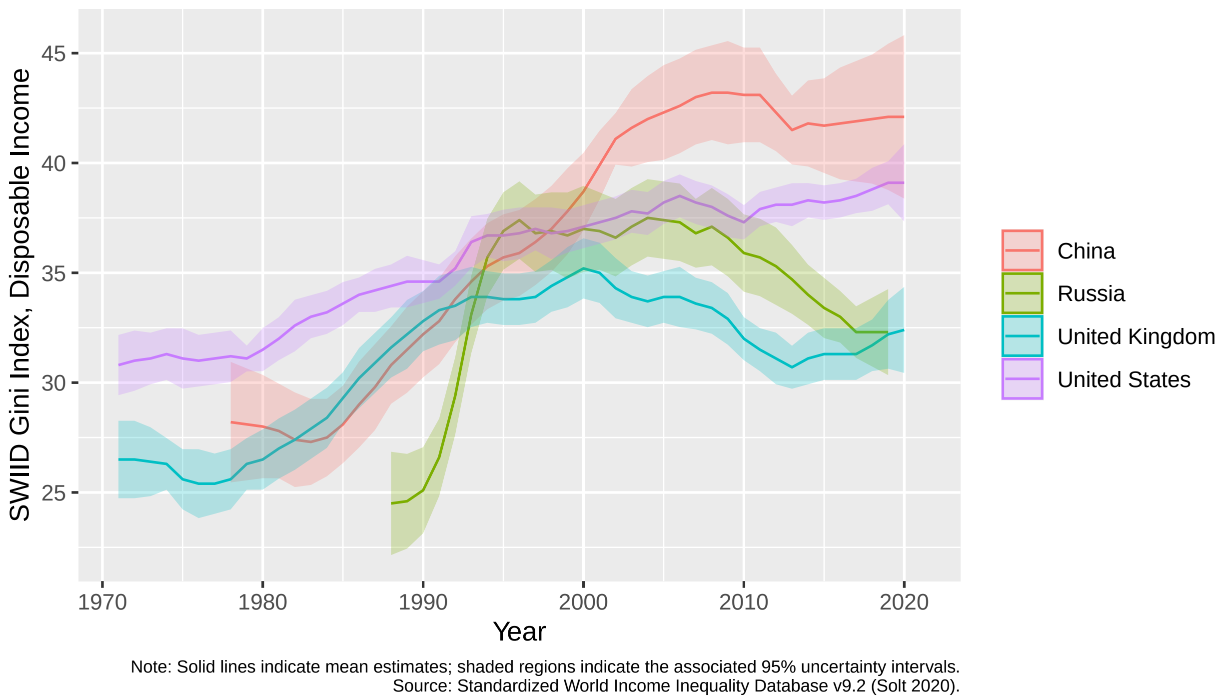


Figure 2.1: The income gap growth in China, Russia, UK, and USA since 1971

mismatch (shown in figure 2.2) from which surplus is created and consequentially proposes an algorithmic solution for the redistribution of these over-produced resources to those without access to them. The solution presented here aims to minimize the cost of redistribution for the producers, minimize waste from over-produced resources (maximize utility for the redistributors), while also maximizing welfare for those that demand but have no access to the over-produced resources.

2.1.1 Summary of Contribution

To the best of our knowledge, using core allocations for the redistribution of surplus or reduction of waste from producers to donation recipients versus independent local donations has not been studied in the algorithmic mechanism design field. However, there exists a number of innovative internet-tech applications that provide platforms for surplus redistribution. We

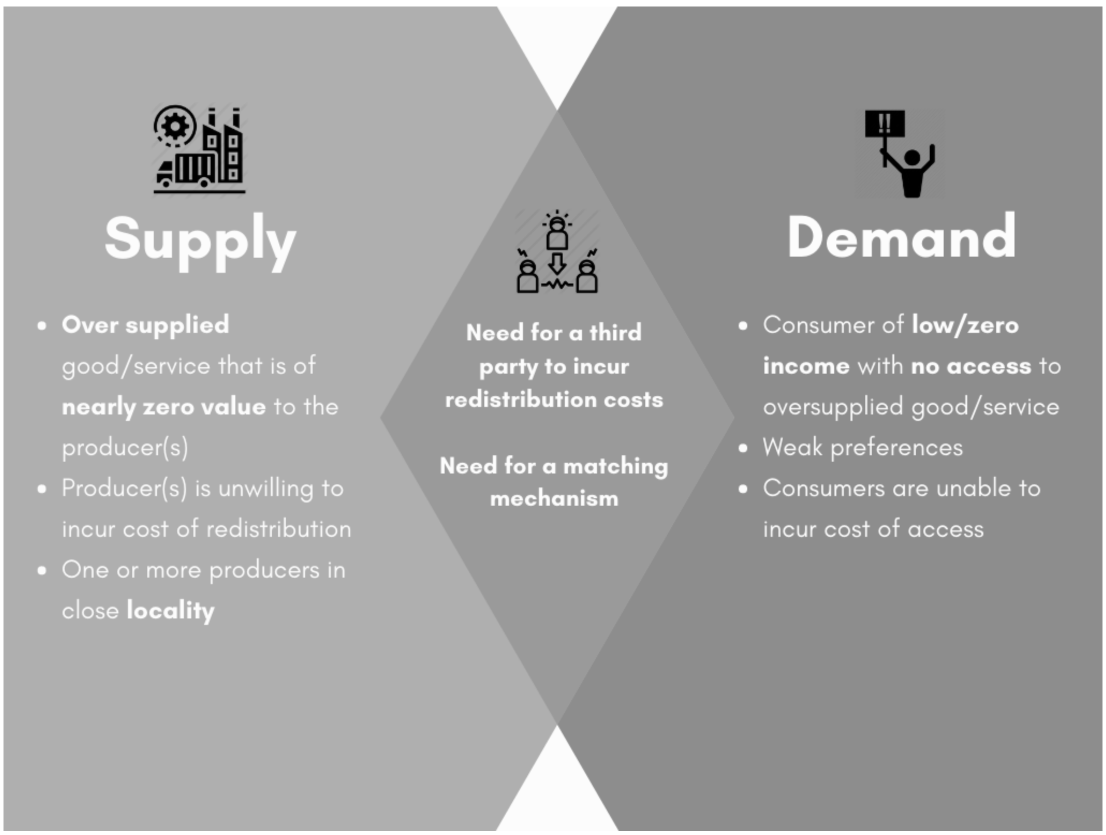


Figure 2.2: The Waste Creation structure

direct the reader to [20, 123] for a survey of these digital applications. The rest of this chapter will further detail the following contributions.

- We examine the creation of waste from overproduction of surplus that is of zero/nearly zero value to producers at the end of a production/market cycle.
- We examine the restriction of access to a resource for the low income classes (zero/nearly zero consumers) through lack of purchasing power at market price.
- We contrast the two options for redistribution, (1) local independent donations between producers and donation centers, and (2) redistribution by way of a global redistributor (what we will call a core redistributor) who collects donations from all available producers and redistributes the surplus to all donation centers respective of their demanded quantities. We show that option 2 or the core allocation maximizes social welfare, and minimizes waste and cost to the producer.
- We also qualitatively study two cases; (1) food waste and food insecurity in the UK, and (2) Los Angeles County's project RoomKey: a pandemic effort to house covid-vulnerable unhoused persons in vacant hotels and motels. Both case studies support the idea of a core redistributor over local independent donation efforts.

2.2 Model

2.2.1 Waste Creation

Overproduction

We begin at the resource producer or supplier (this could be a manufacturer or retailer), and for simplicity we will assume that the resource is a tangible commodity produced for profit, for example baked goods. Due to a mismatch in demand and supply, this resource is over-produced [102, 115, 54]. This is not uncommon. For example, it is common for restaurants, grocery stores, or bakeries of averagely or above-averagely wealthy communities to have excess amounts of over-produced food (probably due to overestimating demand or cost-based planning) that is normally discarded at the end of the day. We will assume that the over-produced resource is either donated or thrown out to the waste bins. At this point, the resource is of nearly zero value to the producer, therefore we will define waste as produce that is of zero/nearly zero value to the producer.

Condition 2.1. *At the end of a production/supply cycle, resources not demanded for consumption are of zero/nearly zero value (waste) to the producer/supplier.*

Consider a utility-maximising producer whose utility (ψ) is represented as follows,

$$\psi = TR(Q_d) - TC(Q_p)$$

Where $TR(Q_d)$ is the total revenue from selling quantity demanded, Q_d, and $TC(Q_p)$ is the total cost of producing quantity, Q_p. We assume that at the end of a production cycle, if $Q_d < Q_p$, then we have an excess quantity(Q_e) produced that is not demanded at the market price of the resource. Since the total revenue for Q_e is zero, i.e,

$$TR(Q_e) = 0$$

The utility from Q_e is then

$$\psi(Q_e) = 0 - TC(Q_e)$$

We see here that the quantity of the resource not demanded at the end of a production cycle yields no utility for the producer, and therefore is of zero/nearly zero value to the producer. A good example of this is bakeries because of their short production cycle but we would argue that fast fashion has created a similar condition for some clothing producers but with a longer production cycle.

Because the resource is of nearly zero value to the producer, who is motivated by utility or profit maximization, the producer is unwilling to incur any cost at all in redistributing or discarding the over-produced good.

Condition 2.2. *A producer is unwilling to incur any cost on an over-produced resource of nearly zero value.*

From Condition 2.1 above, it's trivial to see that the utility has a negative relationship to the cost spent on excess. Since the producers act to maximize utility, they are unwilling to incur further cost because that would increase $TC(Q_e)$, which reduces their utility margin. The case study in Section 2.3 presents evidence that many producers do in fact act this way.

From Conditions 2.1 and 2.2 above, we can see that the producers will seek to minimize cost when dealing with the over-produced resources. Two ways that this can be done are to either dispose of the resource as waste or donate to the nearest most convenient donation spot (which could be a resource bank, soup kitchen, welfare retailer, and so on).

Condition 2.3. *Over-produced resources will either be thrown out as waste or get donated to the cheapest donation spot.*

Let us assume that the producer can only dispose of the excess quantity or donate it to one donation spot in the collection M. If we adjust $\psi(Q_e)$ to include the cost of disposing(DC) or redistributing(RC) the excess resource, then

$$\psi = -[TC(Q_e) + \min(DC(Q_e), \min_{\forall i \in M} RC_i(Q_e))],$$

where RC_i is the cost of redistributing to a donation spot i. We see that whichever one of the two options costs the least will maximize utility for the producer. This means that either disposal, which is normally not an extra cost, or donation to the nearest donation spot will be the options that maximise profit (utility). Later in the case studies, we will show that many producers lack awareness of the options available to them when dealing with surplus, and more often than not simply dispose of the surplus.

Lack of Access

We will assume the existence of a zero to low income population that demands the over-produced resource but does not have the income to purchase it, therefore lacking access to the resource. This is not uncommon given the well documented marginalized populations that lack access to basic resources like food, housing, clothing, among others (we will term these zero/low income consumers).

The zero/low income consumers normally look to donation spots (or sadly waste disposal spots) for access to the over-produced resource.

Condition 2.4. *Low income consumers are unable to access over-produced resource at market price.*

From the law of demand and the linear demand curve, we know the quantity of resource demanded in a perfect market is defined by,

$$Q_p = a - bP$$

Where a and b are constants for factors other than the price of the resource, and P is market price. Considering the consumer is of low income, let us assume the income (I_l) is defined as,

$$I_l \leq \frac{a}{b} \leq P.$$

It is easy to see that even at the upper bound of $I_l = \frac{a}{b} = P$, the quantity demanded is,

$$Q_p = 0, \text{ if } I_l \leq \frac{a}{b} \leq P \text{ is true.}$$

If access to a priced resource is equivalent to ability to afford/purchase the resource (purchasing power), then we see that indeed low income consumers have no access to the over-produced resource at market price.

Condition 2.5. *Resources accessed as donations or waste are demanded at zero/nearly zero prices*

From Condition 2.3 and 2.4, we know that producers will either donate or dispose of the excess resource, and low income consumers that demand the resource can not access it at market price. Therefore, for the disposed resource, it is trivial to see that low income consumers that turn to waste disposals do not intend/expect to pay any price for access to the waste.

And for donation centers, for low income consumers to demand a quantity, $Q_l > 0$, the price (P_e) of the excess resource has to be marked down to,

$$0 \leq P_e < \frac{a}{b}$$

This structure of overproduction of resources that become nearly zero value (surplus) resources, and lack of access to the resource due to zero/low income demand is evident in many industries, most notably, the food industry, and in special cases the housing (emergencies), and clothing (fast fashion) industries as well. The next subsection will set up and propose an algorithmic solution for the redistribution of the over-produced resource. While the above conditions seem obvious, they will be crucial in proving why a core redistribution is the most optimal solution for the problem of overproduction and waste reduction.

2.2.2 Algorithmic Waste Redistribution

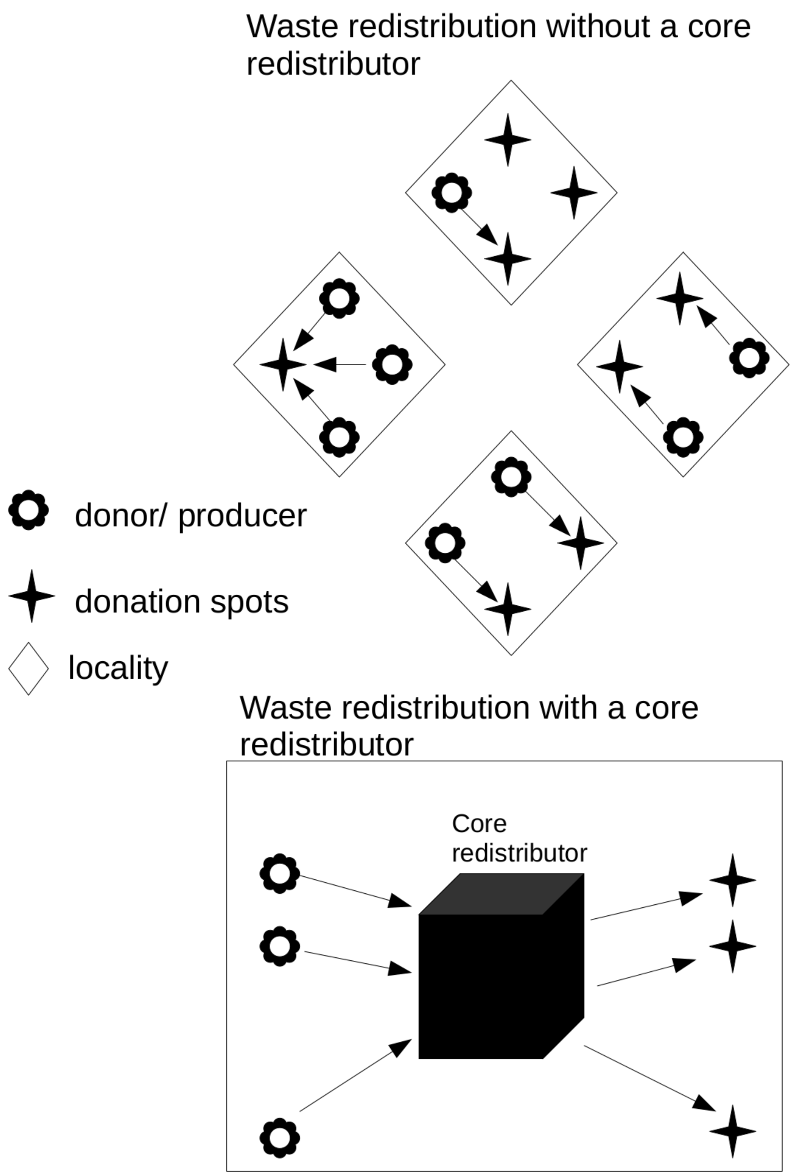


Figure 2.3: The waste redistribution solutions with and without a core redistributor

From the waste creation structure, the producers with the over-produced resource to donate will now become donors in the redistribution model. We are aware of the alternative sources of donations, like private donations from households, but choose to ignore them here for simplicity, as we assume that these individual household contributions are insignificant in comparison to large scale producers. Because the consumers are represented as donation spots in the redistribution model, any zero/low income consumers that look outside of donation spots for resource access are ignored in this model as well. Donation spots could be food banks, goodwill stores, soup kitchens, homeless shelters, and any other centers through which the marginalized receive basic resources in quantities larger than a household. We now set up the redistribution problem.

2.2.3 Formal Model

Let us assume a collection of localities where one locality is specified by some geography, for example, a political city could be a locality and the county being the collection of political cities. Consider M donors in this county looking to donate an over-produced resource, where each donor can donate at most 1 unit of the resource. Each donor also wishes to minimize the cost of redistribution for this over-produced resource which we represent as a utility function on the cost of redistribution

$$\psi_d = \frac{1}{RC(Q_e)}$$

where Q_e is the excess from the quantity produced(Q_p) and that sold, (Q_d). We also define $RC(Q_e)$ as,

$$RC(Q_e) = \begin{cases} 1 & \text{within the same locality} \\ 2 & \text{outside of a locality} \end{cases}$$

Also consider that this county has N donation spots that demand varying quantities of the over-produced resource with each quantity demanded, Q_d units (Each donation spot can have/demand at most Q_d units of the resource). Each donation spot wishes to have enough stock to satisfy the demand from their consumers. Therefore, we will assume that the total demanded units from all consumers at each donation spot is at most Q_d units. Each donation spot has some welfare utility,

$$\psi_w = Q_d - \max(Q_w, Q_{nn})$$

, where the cost Q_w is the waste created at the donation spot and Q_{nn} is the unsatisfied amount of the quantity demanded in case the donated quantity is less than Q_d. We will assume that the M donors and N donation spots are arbitrarily distributed among k many localities within the county. Therefore, each locality (which is a physical geography where the producers (donors) and consumers (donation spots) are located) has some fraction of M and N.

Since the overall goal is to minimize waste($\sum_N Q_w$), we also have a waste utility function,

$$\psi_r = \frac{1}{\sum_N Q_w}$$

A good solution should maximize waste utility, welfare utility, and the donors' utilities. Below we will consider two solutions, one with a core redistributor or central clearing house (like a government or a donation network), and one without a central clearing house or core redistributor (see figure 3.1).

Without a Core Redistributor [WOC]

Theorem 2.1. *If donors/producers look to minimize cost of redistribution, without a third party to carry that cost, the amount of waste grows monotonically with the number of producers, and welfare utility is not maximized*

Proof. We have M donors each donating 1 unit and N donation spots each demanding Q_d units, arbitrarily distributed among k localities. From the definition of $RC(Q_e)$ and

Conditions 2.2 and 2.3, we assume that the donor will always donate within their locality to minimize cost. Since the cost within a locality is the same, each donor i will donate to some donation spot j in the same locality with equal probability,

$$P_{i,j} = \frac{1}{\text{no. of donors in a locality}} \tag{2.1}$$

We can derive the expected utility for each donor, E_i to be,

$$E_i[\psi_d] = -[TC(Q_e) + \min(DC(Q_e), \min_{\forall i \in M} RC_i(Q_e))]$$

$$E_i[\psi_d] = -[TC(Q_e) + 1],$$

where $\min(DC(Q_e), \min_{\forall i \in M} RC_i(Q_e)) = 1$ from choosing to donate to the nearest. Since M and N are arbitrarily distributed among k localities, we will define the number of donors in any one locality as m, where $m \leq M$ and $\sum_k m = M$, and the number of donation spots in that same locality as n, where $n \leq N$ and $\sum_k n = N$.

The probability, $P(X = x)$ that a donation spot, j, gets donations from x many donors in a locality is;

$$P(X = x) = \begin{pmatrix} m \\ x \end{pmatrix} \left(\tfrac{1}{n}\right)^x \left(1 - \tfrac{1}{n}\right)^{m-x} \tag{2.2}$$

We can now derive the expected utility for each donation spot, j, within a locality to be,

$$E_j[\psi_w] = \sum_{x=0}^{m} \begin{pmatrix} m \\ x \end{pmatrix} \left(\tfrac{1}{n}\right)^x \left(1 - \tfrac{1}{n}\right)^{m-x} (Q_d - \max(Q_w, Q_{nn})) \tag{2.3}$$

We can also express $\max(Q_w, Q_{nn})$ as

$$\max(Q_w, Q_{nn}) = |x - Q_d|.$$

From that $E_j[\psi]$ can be rewritten as,

$$E_j[\psi_w] = \sum_{x=0}^{m} x \begin{pmatrix} m \\ x \end{pmatrix} \left(\tfrac{1}{n}\right)^x \left(1 - \tfrac{1}{n}\right)^{m-x} - \sum_{x=Q_d+1}^{m} (x - 2Q_d) \begin{pmatrix} m \\ x \end{pmatrix} \left(\tfrac{1}{n}\right)^x \left(1 - \tfrac{1}{n}\right)^{m-x} \tag{2.4}$$

Notice that,

$$E_j[\psi_w] = \underbrace{\sum_{x=0}^{Q_d} x \begin{pmatrix} m \\ x \end{pmatrix} \left(\tfrac{1}{n}\right)^x \left(1 - \tfrac{1}{n}\right)^{m-x}}_{\text{expected satisfication}} - \overbrace{\sum_{x=Q_d+1}^{m} (x - 2Q_d) \begin{pmatrix} m \\ x \end{pmatrix} \left(\tfrac{1}{n}\right)^x \left(1 - \tfrac{1}{n}\right)^{m-x}}^{\text{expected waste cost}} \tag{2.5}$$

We can now also derive the expected waste for each j,

$$E_j[Q_w] = \sum_{x=0}^{m} (x - Q_d) \begin{pmatrix} m \\ x \end{pmatrix} \left(\tfrac{1}{n}\right)^x \left(1 - \tfrac{1}{n}\right)^{m-x} \tag{2.6}$$

And expected total waste reduction utility,

$$E[\psi_r] = \frac{1}{\sum_{j \in N} E_j[Q_w]} \tag{2.7}$$

Notice that as long as the number of donations $x > Q_d$ for any j, neither total waste reduction utility nor welfare utility are maximized because there will be waste and cost proportional to the difference between x and Q_d. $\square$

Lemma 2.1. *The probability, $P(x > Q_d) > 0$ if $m >> n$*

Proof. From equation (5),

$$P(X = x) = \begin{pmatrix} m \\ x \end{pmatrix} \left(\tfrac{1}{n}\right)^x \left(1 - \tfrac{1}{n}\right)^{m-x} \tag{2.8}$$

The probability that $x > Q_d$ for a certain j becomes,

$$P(x > Q_d) = \sum_{x=Q_d+1}^{m} \begin{pmatrix} m \\ x \end{pmatrix} \left(\tfrac{1}{n}\right)^x \left(1 - \tfrac{1}{n}\right)^{m-x}$$

Which is equivalent to,

$$P(x > Q_d) = 1 - \sum_{x=0}^{Q_d} \begin{pmatrix} m \\ x \end{pmatrix} \left(\tfrac{1}{n}\right)^x \left(1 - \tfrac{1}{n}\right)^{m-x}$$

From Heoffding's inequality for the upper bound of the binomial cumulative distribution function [60],

$$P(x > Q_d) > 1 - \exp\left(-2m(\frac{1}{n} - Q_d\frac{1}{m})^2\right)$$

Consequentially,

$$1 - \exp\left(-2m(\frac{1}{n} - Q_d\frac{1}{m})^2\right) > 0 \tag{2.9}$$

For 2.9 to hold,

$$1 > \exp\left(-2m(\frac{1}{n} - Q_d\frac{1}{m})^2\right)$$

$$\ln 1 > \ln\left(\exp\left(-2m(\frac{1}{n} - Q_d\frac{1}{m})^2\right)\right)$$

$$0 > -2m(\frac{1}{n} - Q_d\frac{1}{m})^2$$

$$0 < (\frac{1}{n} - Q_d\frac{1}{m})$$

$$\frac{1}{n} > Q_d\frac{1}{m}$$

$$m > Q_d n$$

Observe then that $P(x > Q_d) > 0$ if $m > Q_d n$. This is exactly the condition that arises in affluent neighborhoods, where the number of donors/donations is normally much larger than the number of donation spots and their demand ($m >> n$). This creates a scenario where multiple donors in an affluent locality donate to the few donation spots closest to them and therefore create more waste at those donation spots as they are overwhelmed with supply. In this situation, $E_j[Q_w]$ will grow monotonically for the donation spots in localities where $m >> n$. Which directly implies that the expected unsatisfied quantity, $E_j[Q_{nn}]$, for the donation spots in less affluent neighborhoods will grow monotonically as well because m is a fraction of M.

□

With a Core Redistributor [WC]

Theorem 2.2. *With a core redistributor/central clearing house to cover the cost of redistribution and ensure a core allocation [107], virtually all surplus is redistributed (waste minimized), welfare utility, and donor utility are also maximized*

This proof will take two cases, (1) one where the total quantity donated, $\sum_i Q_e$, is greater or equal to the total quantity demanded, $\sum_j Q_d$, and (2) another where $\sum_i Q_e < \sum_i Q_d$. The proofs follow.

Proof. When $\sum_i Q_e \geq \sum_j Q_d$, the core allocation is obtained from a simple algorithm 1 stated below:

Algorithm 1: Surplus redistribution when $\sum_i Q_e \geq \sum_j Q_d$

1. Collect the quantity donated, Q_e from all donors
2. Arbitrarily order all donations spots in a queue
3. Iterate through queue, and allocate each donation spot its quantity demanded, Q_d
4. Terminate when queue is empty

Observe that because $Q_e \geq Q_d$, each donation spot should get exactly the quantity demanded, Q_d. Therefore, for each spot, j,

$$\psi_j = Q_d - \max(Q_w, Q_{nn})$$

And we know,

$$\max(Q_w, Q_{nn}) = |x - Q_d| \text{ and } x = Q_d$$
$$\psi_j = Q_d - 0$$
$$\psi_j = Q_d$$

Observe that this is the maximum possible utility a donation spot can achieve. That leads us to the maximum total welfare utility from the sum of all donation spots, $\sum_{j \in M} Q_{d,j}$

It also follows that the waste for each donation spot, $Q_{w,j} = 0$, and since the cost of redistribution is taken on by the core redistributor, the cost $RC(Q_e)$ for each donor is also 0. In the case where $\sum_i Q_e > \sum_i Q_d$, we will have some surplus $Q_w \equiv Q_e - Q_d$, one could imagine this surplus going to another network of donation spots.

When $\sum_i Q_e \leq \sum_j Q_d$, how a core allocation is found is non-trivial. We will set up the problem as a linear program subject to constraints that ensure a fair allocation with maximum welfare utility and minimum waste. Let $\alpha_{i,j}$ be a variable to ensure that each donation spot and donor are fully satisfied, that is, that each donor's donation is taken and each donation spot gets some quantity that maximises its possible utility. And let $u_{i,j}$ be the utility donation spot j gets from taking donor i's donation. The LP follows:

$$\text{Maximize} \sum_{i,j} (a_{i,j} u_{i,j})$$

$$\text{subject to; } \sum_i (a_{i,j}) \leq 1, \text{for each } j$$

$$\sum_j (a_{i,j}) = 1, \text{for each } i$$

$$0 \leq a_{i,j} \leq 1, \text{for each donation } (i, j)$$

This LP will produce multiple allocations in most cases. We will choose the allocation with minimum waste.

Lemma 2.2. *When $\sum_i Q_e \leq \sum_j Q_d$, a zero waste core allocation always exists.*

Proof. The simple proof is that one can always allocate each donation spot quantity, $Q = (\frac{\sum_i Q_e}{\sum_j Q_d})Q_d$. This is both a fair allocation in terms of equality of the distribution but also ensures no one donation spot j gets $Q > Q_d$, therefore there is no waste created. □

□

Social Welfare and Pareto Optimality

Let's define a total social welfare that depends on the utilitarian assumptions that a society looks to provide resource access to every individual and also minimize resource waste. The total social welfare utility becomes,

$$\psi_{social} = \sum_j (\psi_j - Q_{w,j})$$

From theorem 2.1 and 2.2, because a core redistribution would maximise every donation spot's utility while minimizing the amount of waste created in the redistribution, we can conclude that we do in fact achieve a Pareto improvement on the social welfare with a core allocation. This means that a core allocation would help give low income consumers access to the surplus resource without creating any further waste for the society.

Multiple resources (bundle of items)

If we relax the one resource assumption to allow for multiple resources, one could imagine breaking the bundle of resources into independent resource allocations, where the total utility for all resources is an additive sum of all the independent utilities from each resource. It is trivial to see that the maximization of the independent utilities is a maximization of the total utility.

Cost of Redistribution and Individual Rationality

We make a big assumption that the core redistributor would take on the cost of redistribution, as we imagine some welfare budget is normally available to donation centers through the federal, state, or local governments. The lack of such funding would present a major complication for this model, but we imagine that it would be easier for a network of donation centers to carry the cost of redistribution than individual centers. Future work could explore the implications of the cost of redistribution, for example, why should a donation center in an arbitrary or affluent neighborhood choose to share this cost with other donation centers in a core if federal, state or local government funding is not available?

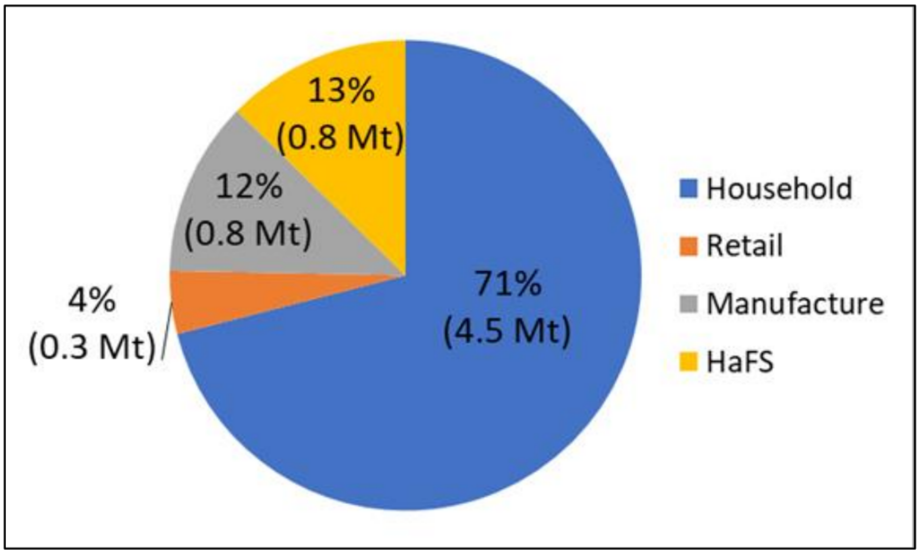
2.3 Case Studies

2.3.1 Food surplus redistribution in the UK

The first of our case studies will look at the concurrent paradoxical existence of food waste and food insecurity in developed countries [50, 115]. The case study will summarize the current state of food waste and food insecurity in the UK (The UK's food waste and redistribution efforts are some of the most studied in the world, making it an easy choice for a case study for this paper). The summary is mainly drawn from data and other resources provided by the Waste and Resources ACT Programme (WRAP). The case study will also examine one of UK's largest food redistributor, FareShare, a non-profit that redistributes food from suppliers to local recipients like food banks and soup kitchens so as to eliminate food waste. This examination of FareShare is done through reviewing FareShare reports and a number of other studies published on FareShare operations in parts of the UK. The case study will conclude with discussion to support the adoption of larger redistribution networks with core allocations.

State of food waste and Food insecurity in the UK

According to WRAP, roughly 3.6 million tonnes of food is wasted annually by the food and hospitality industry in the UK [122, 43]. Further break down shows that over 2 million tonnes of the waste is edible before it becomes waste, what most literature calls *fit for purpose* [122]. FareShare reckons about 1.3 billion meals could be produced from this 2 million tonnes [39]. As shown in figure 2.4, most of this waste is created by households and therefore makes the problem of food waste redistribution that much harder because coordination of collection and redistribution would be much more costly at the household level. Figure 2.4 shows the fractions of food waste created by each sector in the UK. This paper argues for large scale redistribution, nationwide if possible, at the supply level, that is redistribution of surplus from producers (farmers, manufacturers, restaurants and other retailers) to recipients at donation centers (food banks, soup kitchens, shelters, among others) through a core redistributor (like FareShare or Feeding America).



** Food waste at wholesale and in litter is excluded from this analysis as the percentage of inedible parts is unknown and difficult to predict. Data for household also includes waste to sewer, which is not currently available for other sectors.*

Figure 2.4: Amount of edible food waste created by sector in the UK. Source: WRAP [122]

On a positive note, the same 2021 WRAP report shows that the amount of food waste produced in the UK is in fact declinining and is projected to decrease by over 50% by 2030 if the currently proposed steps for food waste redistribution in the UK are met (see Figure 2.5) [122]. However, to meet the goals proposed for waste reduction requires a coordinated effort between academics, policymakers, and involved actors on the ground. This paper aims to contribute solution ideas to such efforts in and beyond the UK, to other countries where food surplus redistribution is not as well established.

This chapter's focus is on the 29% or 2 million tonnes created by the food industry that

	2007*		2018			
	Tonnes	Per capita (kg)	Tonnes	% change	Per capita (kg)	% change
UK total post-farm food waste	11,200,000	181	9,500,000	15%	143	21%
UK post-farm gate food waste (excluding inedible parts)	8,200,000	132	6,400,000	21%	96	27%

** In [Historical changes and how amounts might be influenced in the future]() WRAP 2014, WRAP made the case for a baseline year of 2007 against which to assess changes in UK food waste over time. This was on the basis that a) there is robust data on the largest fraction of UK food waste from that year (i.e. household food waste; ca 70% of the total post-farm gate) and b) this is when the UK began large-scale interventions to reduce food waste (which were aimed exclusively at household food waste until 2010 – with a focus on supply chain food waste commencing under Courtauld 2 in 2010, and in 2012 on food waste from the hospitality and food service sector[18].*

	2007		2018		2030		Reduction in tonnage required to achieve SDG12.3 (2018 to 2030)			% Reduction per capita		
	Total food waste (t)	Total food waste per capita	Total food waste (t)	Total food waste per capita	Total food waste (t)	Total food waste per capita	Wasted food (t)	Inedible parts (t)	Total food waste (t)	2007-2018	2007-2030	2018-2030
Household	8,100,000	132	6,600,000	100	4,400,000	63	1,827,000	373,000	2,200,000	24.2%	52.3%	37.0%
Retail	290,000	5	277,000	4	188,000	3	89,000	n/a	89,000	10.6%	42.0%	35.7%
Manufacture	1,900,000	30	1,500,000	23	1,050,000	15	230,000	220,000	450,000	24.6%	49.9%	33.9%
HaFS	920,000	15	1,100,000	17	685,000	10	363,000	52,000	415,000	-13.7%	32.6%	40.6%
Total	**11,210,000**	**181**	**9,477,000**	**143**	**6,323,000**	**91**	**2,509,000**	**645,000**	**3,154,000**	**20.9%**	**50.1%**	**36.9%**

Figure 2.5: Projections of food waste and surplus in 2030 in comparison to 2007 and 2018. Source: WRAP [122]

could be redistributed as edible food because evidence shows that food disposal is still the default option for suppliers and retailers [80, 25, 53, 42].

FareShare is a UK based non-profit that looks to redistribute edible food, that could be wasted by food producers, to different donation recipients that serve persons facing food insecurity [39, 6]. As mentioned earlier, 1.3 billion meals could be created from the proportion of food wasted by the food industry [39]. According to current estimates from FareShare and Food and Agricultural Organization of the United Nations (FAO), 8.2 million people in the UK struggle to find food [73, 115]. That means the 1.3 billions meals wasted could provide a meal for each one of these 8.2 millions for 159 days of a calendar year. This is exactly FareShare's goal.

FareShare either receives donations from donors who deliver or collects donations from those who can not deliver, then packages and redistributes these donations to local donation spots like shelters, food banks, soup kitchens among others [6]. **Note: Each FareShare independently serves a particular locality.** Within a locality, a FareShare location serves as the core redistributor between local producers and local charities. The case study in [6] showed that barely any waste is created within the local FareShare surplus-donation redistribution. This is clearly shown in Figure 2.6, for the FareShare donation chain in Southampton, UK. Observe that only 8% of the waste created by the suppliers in this Southampton study ended up becoming waste [6]. Evidence from the Southampton study supports the idea of a core redistribution, but of course this data is only local to Southampton. National figures show that FareShare is only salvaging a small fraction of the food surplus wasted and reaching a small fraction of persons facing food insecurity. This could be a result of the fragmentation between FareShare locations, where a collective network effort could cover wider areas and offer core allocation advantages on a wide scale. Figure 2.7 shows the locations of FareShare sites[left] and the distribution of income in the UK[right]. A bird's eye view of these images together seems to imply that FareShare locations are in places of above

Southampton FareShare: 'food flow' summary

Food	(kg)	% total by weight	% re-entering waste stream	% other disposal
Offered	2178	100	0	0
Accepted	2056	94	6	0
Diverted to animal sanctuary	51		0	2
Discarded at FareShare	44		2	0
Given to projects	1961	90	0	0
Preparation-stage waste	392		18	0
Served to clients	1475	68	0	0
Discarded by clients	220		10	0
Other food discarded	94		4	0

Figure 2.6: Food Donation Flow in Southampton with FareShare as the core redistributor. Source: Alexander and Smaje [6]

average income in the UK. But this alone is not enough to explain why FareShare may only be reaching 1.2 million of the 8.2 million people that struggle to find food in the UK. Figure 2.8 shows that there exists quite a number of localities with higher cases of food insecurity and low income that are not covered by FareShare.

Analysis of FareShare's model and UK Food Waste

From the Southampton and London studies of FareShare operations [6], we have evidence that adopting a unified effort to redistribute food surplus has many advantages, best of which is the minimization of food waste. The studies, however, do not give us clear insight into the cost and welfare optimization within Southampton and London. Despite the local success with waste minimization, National efforts are still only achieving minimal surplus redistribution and welfare maximization (Evident from the 8 million that still struggle to find food in the UK). One of the biggest challenges for food waste redistribution is the difference in goals of the actors involved. This is perhaps why "FareShare still only has capacity to

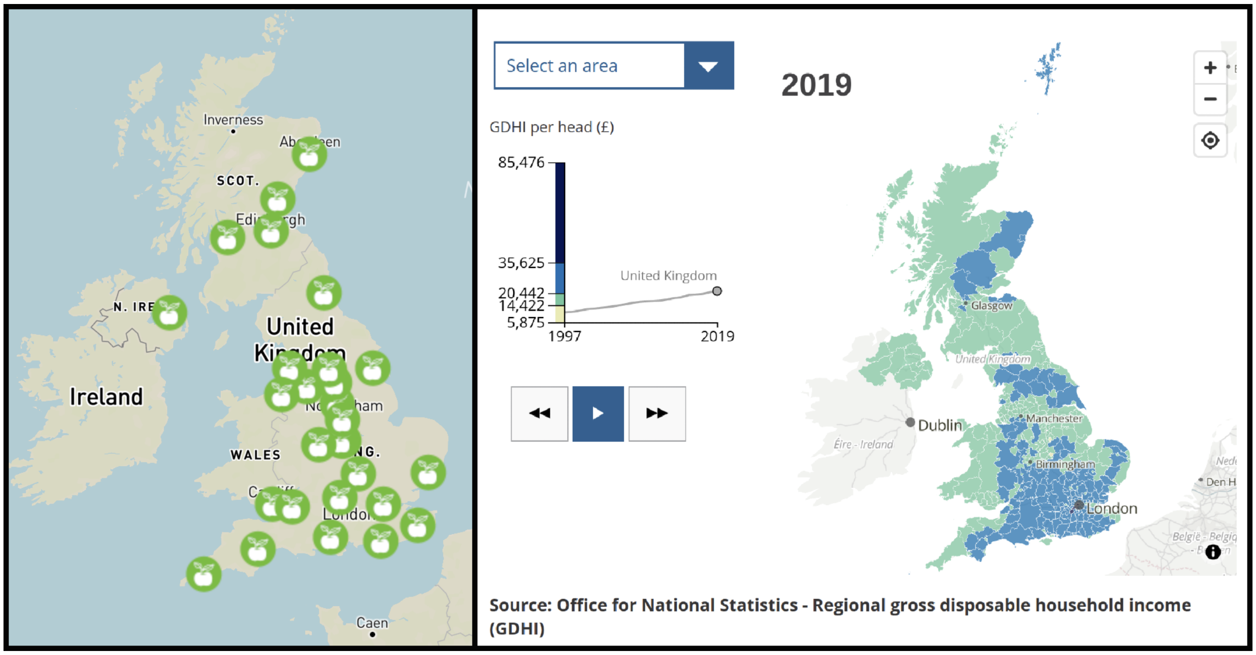


Figure 2.7: LEFT:Map showing FareShare locations in the UK [41]. RIGHT: Map showing Income distribution in the UK. Source: of National Statistics [88]

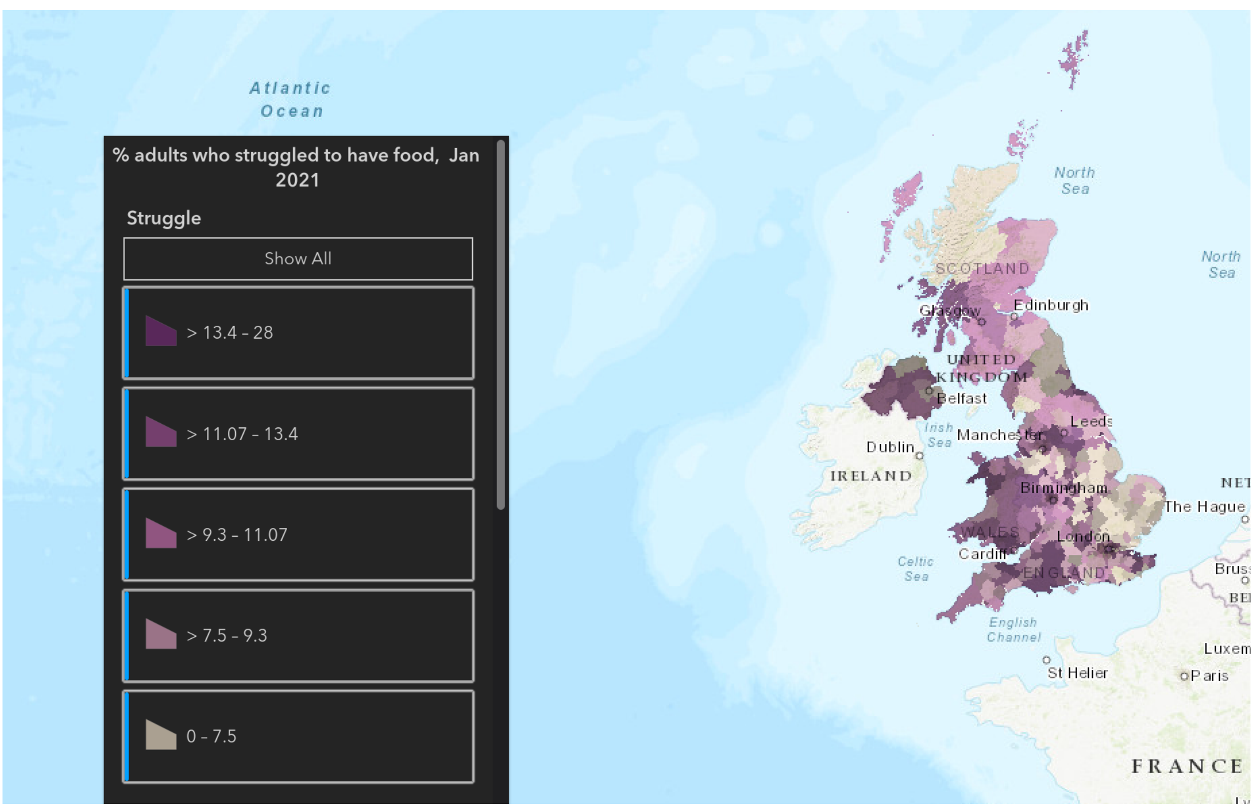


Figure 2.8: Map showing food insecurity in the UK. Source: Fareshare [40]

handle about 5% of supermarket surplus—equivalent to some 36 million meals—to avoid it becoming food waste (FareShare, 2018). There remains a good deal of work to be done to effectively handle the remaining 95%" [100]. Thapa Karki et al. [115], Facchini et al. [36], Diaz-Ruiz et al. [32], Ciulli et al. [25], Facchini et al. [37] further prove that the failures of food redistribution at micro-levels (localities) are mainly due to independence between efforts keeping them local and fragmented. Perhaps a more macro-level approach to food waste redistribution (core redistribution) like one proposed by this paper could be the best path to that 2030 50% food waste reduction goal.

Of course, there are more limitations to the redistribution of food surplus beyond algorithmic or engineering problems. The FareShare study showed that some suppliers are unaware of donation as an option for surplus redistribution [6, 42]. While among those that are aware, most feel pressure to resell waste at discounted prices due to the revenue maximisation requirements of their corporate owners, to whom redistribution of food surplus is not viable [6, 44, 25, 42]. Furthermore, many producers cite the fear of liability claims as the biggest reason why they choose not to donate [6, 80, 44, 25, 42, 96]. This, however, is one factor that could be solved with a core redistributor who can standardize and regulate the quality of donations sent to recipients so that donors are spared the cost of standardization and the liability from failure to do so. FareShare stands as evidence of this [6]. Difficulties in predicting supply and demand can also be best dealt with by a core redistributor. This is shown in Davis et al. [28] who propose the use of time series models to predict food donation behavior at 6 different brokerage food banks in the US to within 10% accuracy loss. Davis et al. [28] also show that it is easier to generate food donation forecasts with higher accuracy at a network level than at the decentralized level. Further empirical evidence for the need of third party redistributor is given by, Phillips et al. [98], who show that the costs for redistributing the surplus can be offset by large recruitment of suppliers and recipients under on core redistributor. This can be done by expanding the core redistributor's locality. We advise the reader to look at [98] for a numerical examination of food redistribution with localities, and at Alexander and Smaje [6], Thapa Karki et al. [115], Ciulli et al. [25] for further discussion of the limitations of food surplus core redistribution.

2.3.2 Housing waste redistribution in LA county (Project Roomkey)

Emergency situations provide the most clear-cut evidence of the oversupply-lack of access systematic mismatch highlighted by this text. That is, in cases of natural disasters and other emergency situations, low income communities are normally left without resources in high demand while high income places are left with oversupply of the same resources (Puerto Rico after hurricane Maria and New Orleans after hurricane Katrina are two popular examples) [52, 48, 59, 51]. This has been evident in the COVID-19 pandemic as well. Therefore, this case study will explore emergency housing during the COVID-19 pandemic. We will particularly focus on LA county's Project Roomkey, "a collaborative effort by the State, County, and the Los Angeles Homeless Services Authority (LAHSA) to secure hotel and motel rooms for vulnerable people experiencing homelessness. It provides a way for people who don't have a home to stay inside to prevent the spread of COVID-19" [87]. Here we will follow the same structure as the food waste case study, beginning with a look at the state of Project Roomkey and how it relates to this paper's proposed hypothesis on oversupply and lack of access. We will follow that with an analysis of Project Roomkey in relation with theorem 2.

State of Project Roomkey

During the early months of the pandemic (March 2020 - October 2020), most of the US mandated state-wide lockdowns so as to slow down the spread of the coronavirus. These lockdowns had unessential businesses shutdown and everyone besides non-essential workers were asked to stay at home. This meant that **hotels and motels around the country were left with an oversupply of vacant rooms (low value supply)** [105, 7, 94]. However, while the majority of the world could shelter in, **the houseless were left vulnerable to the coronavirus (low income demand and lack of access to housing)**. Project Roomkey is the collaboration between the state of California, city of LA, and LAHSA, under which vacant rooms were acquired to house eligible houseless persons. The assignment was done using Algorithm 5 [12].

Algorithm 2: The assignment procedure employed by LAHSA under Project Roomkey

Organize agents in some priority list
for *Each eligible agent on the list* **do**
- Assign agent to a local homeless service provider
- The local homeless service provider assigns the agent a housing option according to their needs

end

Eligibility and priority for assignment of interim housing under Project Roomkey are determined by "high-risk profile for COVID-19"[12]. According to LAHSA, high-risk is defined or determined by age, chronic health condition, COVID-19 asymptomatic condition, persons currently staying in congregate facilities. A priority list is generated from the above criteria [12].

Initially, the city projected that they would house over 15,000 of the LA area's 60,000 unhoused persons [12]. However, as shown in figure 2.9, only about 30% of this goal was achieved before it was shutdown in late 2020. LAHSA's leadership cited a lack of personnel and funding as the reason it did not succeed [112]. Analysis below will show that there were also some inefficiencies in their room allocation procedure in algorithm 5.

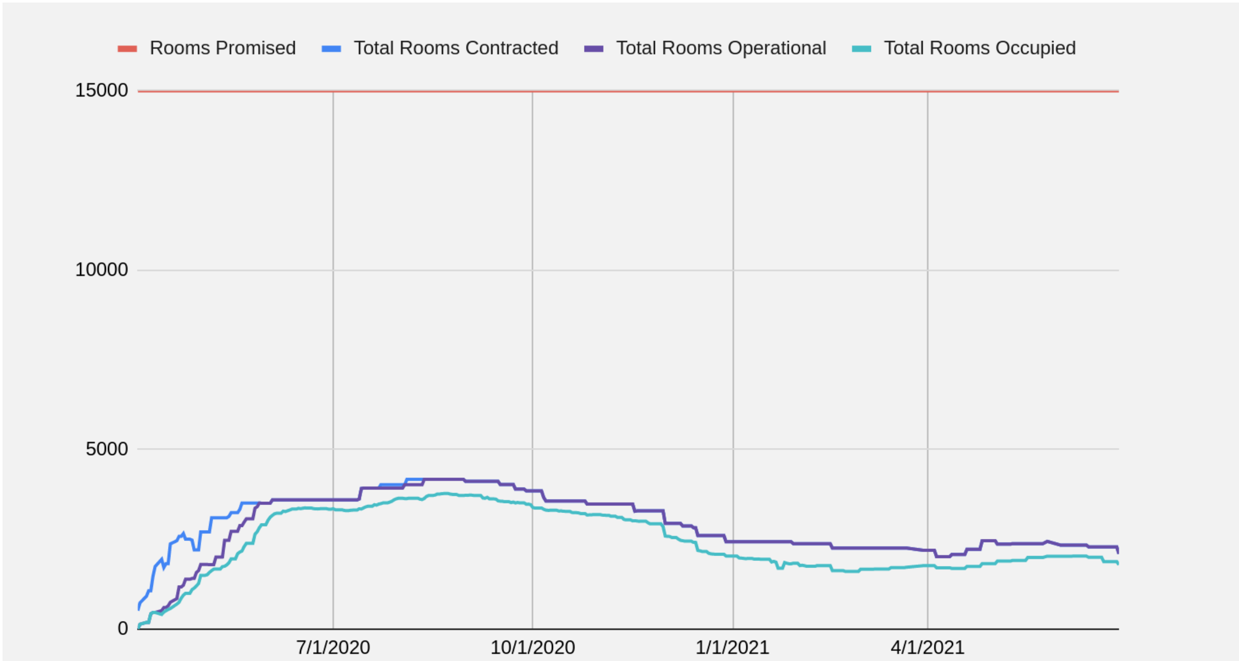


Figure 2.9: LA County Project Roomkey Tracker [116]

Analysis of Project Roomkey

The immediate point of note is that preferences and assignments are restricted by locality from the fact that the housing options are distributed among local homeless service providers who oversee the local hotel and motel room matching [12]. While LAHSA is in the position of a core redistributor, their role in the matching only goes as far as acquiring the vacant rooms, but the matching of persons to these rooms is done by on-site service providers.

From figure 2.9, we see that throughout the entire lifetime of Project Roomkey, the number of rooms contracted was consistently higher than the number of rooms occupied, despite the number of houseless folks being much higher than even the number of projected rooms. It is trivial to prove that with a core redistributor, the number of contracted rooms would be easily equal to the number of occupied rooms. That is, the amount of waste would be minimized. Aguma [3] shows that a core allocation, for this Project Roomkey assignment problem, would achieve Pareto optimality, that is, a core allocation would maximise individual social welfare given some priority ranking on the persons seeking vacant rooms (note that a priority ranking is already weakly-established by LAHSA's eligibility list). Additionally, LAHSA, the state, and LA county, as the third party redistributor, incurred the cost of redistribution, that is, contracting rooms and covering transportation costs to the vacant rooms [12]. We advise the reader to look at [3] for a comprehensive examination of Project Roomkey in contrast to a core redistribution, and [105, 7, 94] for the successes and failures, outside matching algorithms, of hotel housing during the pandemic.

2.4 Conclusion

2.4.1 Discussion

This text examined the paradoxical mismatch where both overproduction of highly demanded resources and a lack of access to the same resources exist within the same communities. We have shown that the surplus created, normally from overestimation of demand and/or cost reduction planning for the resource, is of zero to low value for the producer because it yields zero or negative utility with respect to revenue returns and cost. For a producer looking to maximize profit, the rational option for dealing with this surplus has to be the cheapest one, which, from evidence in the food surplus case study, is normally waste disposal. We also proved that for those in zero to low income classes, there is a lack of access to the oversupplied resource at market price because purchasing power determines access. They therefore turn to donation/welfare centers to access these sometimes essential resources. How this surplus is redistributed to donation centers is crucial to waste and cost minimization, and welfare maximization.

We propose the adoption of a core redistribution wherein a third party like the federal or local government or a network of donation centers collects all the surplus from producers and appropriately redistributes it to donation centers. The core redistributor incurs the cost of redistribution which, again from evidence from FareShare and project Roomkey, is plausible. We showed that this core allocation maximizes welfare for the donation centers, minimizes cost to the producer, and minimizes waste created within the supply chain. This is backed by evidence in the UK food waste redistribution case study in section 3. That is, a study on the operations of FareShare in the city of Southampton showed that the amount of waste created between redistributing surplus from donors to donation recipients is about 8% of the total surplus. This is, however, not the case when we look at the picture on a national scale, where FareShare locations and other redistribution efforts remain fragmented and independent of each other. A similar picture is seen in the case study of project Roomkey in section 3.2. Evidence of mismatches, unfilled rooms despite higher numbers of unhoused persons, and 30% success rate could all be attributed to adoption of local matching producers over a core allocation overseen by the city of LA. Below we offer a summary of recommendations for surplus redistribution of essential resources like food, clothing, and housing.

Recommendations for surplus redistribution

- *Existence of a third party redistributor.* This is necessary for a core allocation and perhaps why organizations like FareShare and Feeding America have been more successful than smaller independent efforts.

- *Government policy.* The core redistribution is easiest as a national government undertaking otherwise there needs to be policy to regulate and protect the operations of the third party redistributor and producers, in terms of liability, tax write-offs, and subsidies to fund the cost of redistribution.

- *Investment in supply and demand predictions.* Evidence from the case studies showed that a healthy knowledge of how much surplus for redistribution, and how much demand for the surplus there is, are key to successfully minimizing waste and maximizing welfare.

- *Creation of awareness*. Lastly, there has to be considerable effort put into making the public aware of the existence of these core redistributors and the benefits of redistributing surplus through a core redistributor.

2.4.2 Limitations

There are factors beyond locality that affect surplus redistribution that are not considered here, the biggest of those being the politics of welfare efforts. Policy and government intervention is key for surplus redistribution and waste minimization, but there is rarely sufficient support of that nature.

Additionally, the claim of zero or nearly zero value of surplus at the end of a production or supply cycle ignores value outside profit, like social value from donating surplus, feeding employees, or any other forms of value. However, we believe considering these other forms of value beyond profit does not have significant effect on the model proposed here.

The text also assumes that donation centers consider waste reduction a priority, but that is not always the case because some donation centers only care for satisfaction of their demand and growth. Both of which are affected by waste reduction, but that is not always obvious to local donation centers. This text also assumes that a third party, like, a federal or local government would avail funds for the cost of redistribution. Future work could explore how a network of donation centers would collectively cover this cost and what that would mean for their utilities.

Another limitation is that this text doesn't properly address the definition of surplus or what is considered waste. Evidence from the UK food waste case study shows that confusion between "best by" and "use before" labels is one of the biggest sources of waste creation. That issue and others related to definition or categorization of what is surplus or waste have not been addressed in this text because those definitions are domain specific and this text is meant as a general guide for surplus redistribution.

Lastly, multiple reports showed that the largest proportion of consumer waste is created by households, but this research only looks at redistribution of surplus from producers. Perhaps future work could investigate and propose solutions for redistribution of surplus accumulated by households.

Chapter 3

Matching Mechanism for assigning housing to low-income persons

During this pandemic, there have been unprecedented community and local government efforts to slow down the spread of the coronavirus, and also to protect our local economies. One such effort is California's project Roomkey that provided emergency housing to over 2000 vulnerable persons but fell short of the set goal of 15,000. It is projected that the homelessness problem will only get worse after the pandemic. With that in mind, we borrow from efforts like project Roomkey and suggest a solution that looks to improve upon these efforts to efficiently assign housing to the unhoused in our communities. The pandemic, together with the project Roomkey, shed light on the underlying supply demand mismatch that presents an opportunity for a matching mechanism solution to assigning housing options to the unhoused in a way that maximizes social welfare and minimizes susceptibility to strategic manipulation. Additionally, we argue that this automated solution would cut down on the amount of funding and personnel required for the assignment of housing to unhoused persons. Our solution is not intended to replace current solutions to homeless housing assignments but rather improve upon them.

3.1 Introduction

In this global pandemic, humanity as a collective has been awakened to what is most important to our unified survival. Now more than ever, we understand the significance of a permanent shelter to call home. However, while many of us could stay indoors and protect ourselves and our communities from the spread of the virus, those unhoused among us were and are still left vulnerable. The United States Department of Housing and Urban Development reported the homeless population to be over 500,000 across the nation[46]. Of these 500,000, Culhane et al. estimate that the modal age to be between 50-55 in several cities[31] and this coincides with the most COVID-19 vulnerable group as reported by the Center for Disease Control(CDC). To further emphasize this vulnerability, a 2019 study found that 84% of the unhoused population self-reported to have physical health conditions[65]. California and New York, states that have been gravely affected by COVID-19, also have the largest unhoused populations. This summary does not even tell the global story which paints an even bleaker picture.

Los Angeles and many other cities scrambled to provide temporary housing for the unhoused during the pandemic through tent cities and vacant hotel rooms[62]. However, most of these were either poorly assigned, as in the case of disabled persons, or left vacant because of the lack of an efficient allocation procedure. This metropolitan effort also leaves a few questions unanswered, for example, what happens after this pandemic? How many other people will be left unhoused? How many additional housing options will become available for low-income persons? To answer some of these questions and meet the need for a better housing assignment procedure, we propose a matching mechanism to improve the allocation of available housing to unhoused marginalized groups such as veterans and low-income families. In the background, we review LA county's project Roomkey initiative and set the stage for a matching mechanism that could improve this initiative.

3.1.1 Background

Case Study: Project Roomkey

According to the LA county COVID-19 website, project Roomkey is "a collaborative effort by the State, County, and the Los Angeles Homeless Services Authority (LAHSA) to secure hotel and motel rooms for vulnerable people experiencing homelessness. It provides a way for people who don't have a home to stay inside to prevent the spread of COVID-19" [87]. Eligible persons, where eligibility is determined on the basis of vulnerability to COVID-19 and a reference from a local homeless shelter or law enforcement office, are assigned temporary housing in the form of hotel and motel rooms.

The matching of eligible persons has been done by local homeless shelters that match the individuals to available hotel or motel rooms in their locality. Whether this is automated is unclear, but given the program's failures, one would assume that the matching was NOT done by a central clearing house but rather arbitrarily without full knowledge of preferences and optimal matches.

Furthermore, the program was not clear on how individuals would be moved to permanent or transitional housing when it closes. To quote the website, "while participants are staying at these hotels, on-site service providers are working with each client individually to develop an exit plan, with the goal of moving them to a situation that permanently resolves their homelessness. In cases where this isn't feasible, LAHSA will use existing shelter capacity to move people into an interim housing environment or explore other options"[87]. The key part is "on-site service providers are working with each client individually," which implies that the matches are not automated and were made depending on whatever information was locally-available to the on-site service provider. The LA Times has highlighted some failures in the project, for example, the project was slammed for discriminating against the elderly and disabled because," the agency deliberately excluded those who cannot handle their own basic activities, such as going to the toilet or getting out of bed"[111]. The project's leadership cited a lack of personnel and funding as the reason it did not succeed[112]. So clearly, a cheap and automated option for matching individuals to housing options is required.

The project is now coming to an end after housing about 30% of the projected total. While the program has been reported as a failure, it allows one to imagine a real solution to homelessness in LA county and in fact, any metropolis. What the program showed is that there is room for a central matching mechanism that can help move persons from the streets into shelters and from shelters into permanent housing. What we will show below, is that this mechanism can be designed to be Pareto-optimal (assign every person their best possible option at the time of assignment) and strategy-proof (persons cannot do better by cheating in this mechanism). Given a lack of funding and personnel, we felt that an automated matching mechanism that is theoretically optimal would be a great solution.

Further analysis of project Roomkey reveals a rich structure that reinforces the need for a matching mechanism. Chapter 2 gives a detailed look at this structure. We will now summarize how it applies to project Roomkey. Because of state and federal mandated lockdowns, hotels and motels found themselves with large volumes of vacant rooms, an oversupply of sorts. In the same communities as the oversupplied hotel and motel rooms are the many unhoused folks that, due to different circumstances, can not afford to access and pay for the vacant rooms but do demand shelter, more so in a pandemic with federal and state-mandated lockdowns. What we see here is an oversupply of a commodity/service, and an abundance of demand but the two sides are inaccessible to each other without the help of a third party, which in the case of project Roomkey, was the California State and LA local government. This third party is what we consider as the matching mechanism designer whose design matches unhoused folks to the vacant rooms. This text, therefore, intervenes at this design point, to further highlight the structure of oversupply and handicapped demand.

We will go on the suggest simple but sophisticated matching mechanism that can satisfy the locality constraints that arose in the allocation of vacant rooms to unhoused persons.

A Brief Review of Relevant Housing and Homelessness Literature

This chapter contributes to a well-established body of work on homelessness, matching markets applied towards social good and matching mechanisms specifically for housing assignment. Below we review a few key papers on the above-mentioned research topics.

While we highlight the need for a matching mechanism to mitigate homelessness in cities around the globe, there is a long history of scholars deploying matching or mechanism design towards efficient housing solutions. We will summarize some relevant and notable works here.

Scholars of mechanism design have been studying housing matching markets from as far back as 1974 when Shapley and Scarf put forth economic mechanism theory for the housing market with existing tenants and introduced the Gale Top Trading Cycles algorithm[107]. In 1979, Hylland and Zeckhauser set the foundation for a house allocation problem with new applicants, defining a housing market core[63]. Abdulkadiroglu and Sonmez extend the work to a model with new and existing tenants[2]. We direct the reader to [1] for a more comprehensive review of matching markets theory.

O'Flaherty goes beyond economic game theory to provide a full economic "theory of the housing market that includes homelessness and relates it to measurable phenomena"[89]. He later extends the work to answering "when and how operators of shelters should place homeless families in subsidized housing"[92] and also updates the economics of "homelessness under a dynamic stochastic framework in continuous time"[93].

Sharam gives a comprehensive breakdown of how matching markets have been applied towards the provision of new subsidized multifamily housing for low-income families in Australia[109].

Sharam also illustrates ways in which the use of digital platforms for matching could help improve the optimality of matching in housing assistance[108]. To the best of our knowledge, [109] and [108] are the only texts that explore the use of a matching mechanism for the provision of low-income housing. Sharam, however, does not extend the work to marginalized groups and only considers the Australian effort whereas we look to create a mechanism that not only looks at low-income multifamilies but all unhoused persons.

Because of the overwhelmingly unstable labor and the housing market at the present, Hanratty's work on the impact of local economic conditions on homelessness using Housing and Urban Development(HUD) data from 2007-2014[57] is also very relevant to our research. Mansur et al., which examines policies to reduce homelessness, will be useful for the future work in this research that concerns itself with policy recommendation[77].

Our contribution

Building from all this past work and the unique structure of the project Roomkey, we provide a matching mechanism for better interim and/or permanent housing assignments for unhoused individuals. This mechanism is derived from those explored in [107],[63], and [2]. To the best of our knowledge, matching mechanism design has not been studied in the algorithmic game theory literature. We show that our simple mechanism is also Pareto-optimal and strategy-proof within the context of allocation of housing to the unhoused.

3.2 Model

3.2.1 Problem Formulation

Consider a metropolis where n agents, which would be persons without permanent housing, ranging from multifamilies to single individuals entered in a shelter or veteran affairs database, looking to transition to better housing options. Let us further assume a m available housing options in many forms: low rent apartments, vacant motels or hotels, tent cities, or group homes (many housing options of this kind were acquired or created by local governments during the COVID-19 lockdown). A person i has a preference list $(\pi_i(j))$ on the housing options which is derived from their individual preferences on size, location, cost, accessibility, and many others. We assume that there is no preference list on the persons as that could open the model up to circumstantial bias. However, we assume that there exists a priority ranking, R on the agents on basis of factors like family size, health risk like the current COVID-19 risk for elders, time spent waiting for a housing assignment. How R is determined is left up to the decision maker like the Veteran Affairs office or city officials. (In fact, most shelter or housing authorities almost always have such priority lists already. For example for COVID-19 emergency housing, persons under the highest COVID-19 risk were given top priority.)

Research goal

The goal then is to design a mechanism that matches the n persons to the m housing options according the preference lists and priority ranking while considering that $n = m$, $n > m$, or $n < m$. Because we intend to implement this model with local policy makers, we have the additional goals of minimizing cost of implementation and personnel required.

With a model defined and a research goal specified, the next section details how this goal is

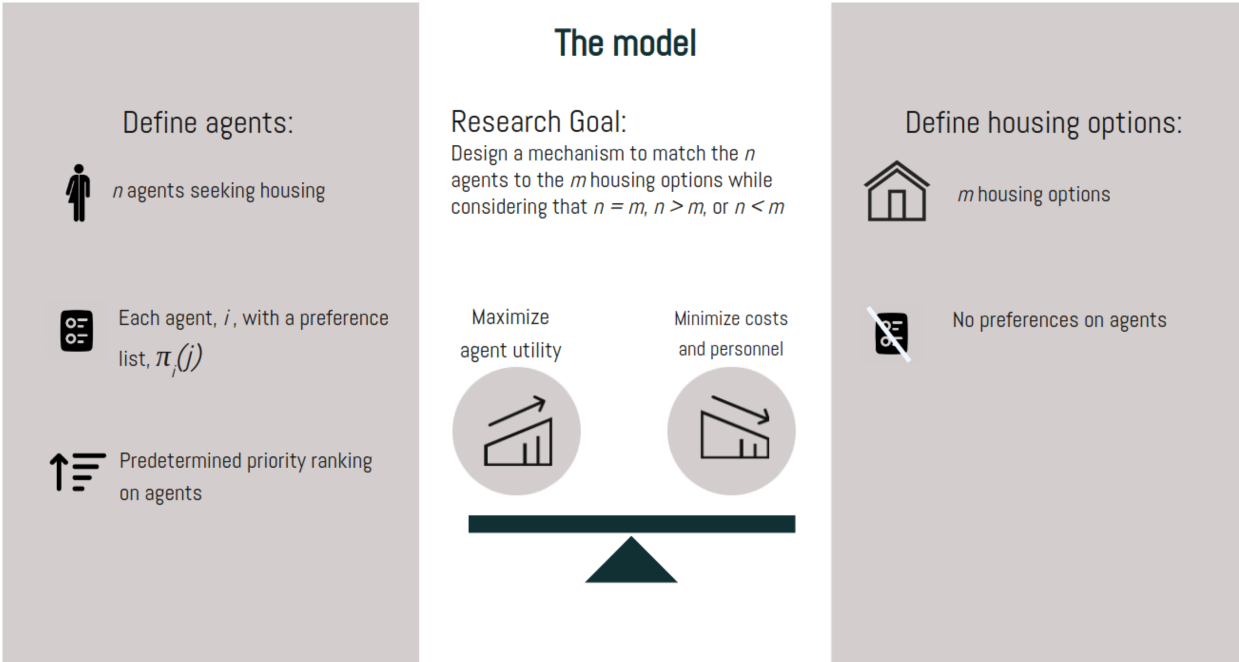


Figure 3.1: The housing matching model

attained using a simple matching algorithm. Analysis of that algorithm's effectiveness is also included in the next section.

3.3 Matching mechanism and analysis

In the last section, we established that there are three cases expected in this matching problem. We will give an algorithm for each one of these here, starting with the most straightforward case where $m = n$, then explain how simple modification can help tackle the other two cases.

For the case of $n > m$, the last $n - m$ agents in the priority queue simply maintain their current housing options. So, in a sense, we tackle this case the same way we go about the $m = n$ case. This is also true for $m > n$, where the $m - n$ least preferred housing options are simply left unassigned. A definition and proof for Pareto optimality follow.

Algorithm 3: A matching algorithm for assigning housing to the marginalized when $m = n$

Organize agents in some priority queue in descending order (ties are broken randomly)

for *Each agent in the queue* **do**

1. Assign them the best housing option currently available according to their preference list

2. Terminate when queue is empty

end

3.3.1 Pareto optimality

Theorem 3.1. *The simple Algorithm 3 produces a Pareto optimal allocation,* $X = (x_1, x_2, x_3.......x_n)$ *in all three cases;* $m < n, m = n$, *and* $m > n$. *Where* $x_i = j$ *is the housing allocation of option* j *to agent* i.

Proof. Let us assume that X is not Pareto-optimal. This means X is dominated by another matching assignment X' in which at least one agent j must have a better and different allocation a. But we know that X assigns every agent their best available preference at the time of assignment. So if j indeed has a better assignment in X', this would mean that an agent i (who got the assignment a in X) earlier in the priority queue also has a different assignment in X'. Observe that agent i's assignment is either worse in X' or must be an assignment that was awarded to another agent earlier in the priority queue in X. One can follow this cycle until at least one agent gets a worse off assignment in X'. This presents a contradiction because now we see that either j does better and another agent does worse in X' or j themselves gets a different option that is not their best available option, in which case they would do worse in X'. Therefore, it is impossible that X' dominates X. To illustrate this better, we provide a few examples below. □

Example 1: $m = n$

Given an agent set i, j, k, and housing options a, b, c. With a priority queue: $i - j - k$ and preference lists:

$$i : a \succ b \succ c \tag{3.1}$$

$$j : b \succ c \succ a \tag{3.2}$$

$$k : c \succ a \succ b \tag{3.3}$$

Our algorithm would assign housing options as follows, $x_i = a, x_j = b, x_k = c$. All three agents would get their best options and so any other algorithm must either produce the same assignment or at least one agent would be worse off.

if we altered the preference lists to:

$$i : a \succ b \succ c \tag{3.4}$$

$$j : a \succ c \succ b \tag{3.5}$$

$$k : c \succ a \succ b \tag{3.6}$$

Our algorithm would assign housing options as follows, $x_i = a, x_j = c, x_k = b$. Observe that in this case j and k do not get their best possible assignment but get the best available assignments. If another algorithm gave j housing option a, then i must get a different assignment and hence be worse off.

We ask the reader to try out different permutations of the preference lists and check to see that in each, no other assignment would dominate that produced by algorithm 1 given in this text.

Example 1: $m < n$

For the case where, $m < n$, the same algorithm is employed but this time the $n-m$ remaining agents in the priority queue simply maintain their existing housing options or, more harshly put, do not get a new housing option.

Consider an agent set i, j, k, l, and housing options a, b, c. With a priority queue: $i - j - k - l$ and preference lists:

$$i : a \succ b \succ c \tag{3.7}$$

$$j : b \succ c \succ a \tag{3.8}$$

$$k : c \succ a \succ b \tag{3.9}$$

$$l : a \succ c \succ b \tag{3.10}$$

Our algorithm would assign housing options as follows, $x_i = a, x_j = b, x_k = c, x_l = None$. Any algorithm that gives l any of the options a, b, c would leave another agent worse off, unless the number of housing options increased.

3.3.2 StrategyProofness

A matching mechanism is strategy-proof if truth-telling is a utility-maximizing strategy, that is, the only way an agent can be guaranteed to get their best possible assignment is if they report true information.

Theorem 3.2. *Algorithm 3 is strategy-proof because the only way an agent gets their best option is by picking it in their turn.*

Proof. Let us assume we have three agents i, j, k with that exact order in the priority queue,i.e;

$i - j - k$. With housing options a, b, c, lets also assume their true preferences are as follows;

$$i : c \succ a \succ b \tag{3.11}$$

$$j : c \succ b \succ a \tag{3.12}$$

$$k : b \succ a \succ c \tag{3.13}$$

The algorithm would assign housing options as follows, $x_i = c, x_j = b, x_k = a$ (The reader can check for Pareto optimality). But if agent j misreports their preferences as $j : a \succ b \succ c$, they would get a when their best option c was available. In fact, if j alters their preference list in any way, they would never do better than when they correctly report their preferences (We invite the reader to try out different orders of preference over a, b, c for agent j). We, therefore, can say this algorithm 3 is strategy-proof. □

3.4 Project RoomKey Revisited

In this section, we will investigate how the algorithm proposed by this text compares to the current algorithm employed by LAHSA for assigning housing under project Roomkey. Of course, LAHSA does not officially call their procedure an algorithm or have a clear outline of steps taken in assigning housing options. We had to read through their program policies and procedures [12] and decipher some outline of the implicit algorithm they use for the assignments.

Below, we will present preliminaries to that algorithm including the non-trivial structure that allowed for the proposal of project Roomkey, the project's priority criteria, the algorithm itself, and an analysis of it.

3.4.1 The Over Supply, Low-income demand connection

As a precursor to further evaluation of project Roomkey, we would like to highlight the unique structure that rendered project Roomkey necessary.

We have a producer that has an **oversupply of a commodity or service**, and because of the oversupply, the commodity/service is of **nearly zero value** to them. The pandemic created this situation for hotel and motel owners who suddenly had an abundance of rooms, that in many places around the world, were left unused.

Adjacent to this is the demand that by different circumstances, is rendered unable to access the oversupplied commodity/service. Circumstances like low to zero income to purchase a commodity that the producer would rather waste than avail for cheap or charity. In many cities around the world, unhoused persons could make use of these rooms but can not access them because there is rarely a third party (or producer) willing to incur the cost of redistribution. This is the scenario that created the vacuum for project Roomkey to fill.

With California state and local governments stepping in to incur the cost of redistribution, this matching of oversupplied commodities/services to handicapped demand happens. The one-step left to reconcile then is, how to efficiently match the vacant rooms to the unhoused folks. Below, we will compare project Roomkey's matching procedure to the one proposed by this text, in the context of Pareto optimality and strategyProofness.

3.4.2 Project Roomkey Housing assignment

From [12], given n eligible unhoused persons and m housing options **distributed among different homeless service provides**, and a priority list,mu the algorithm for assignment is as follows:

Algorithm 4: The assignment procedure employed by LAHSA under project Roomkey

for *Each agent in mu* **do**
- Assign agent to a local homeless service provider
- The local homeless service provider assigns the agent a housing option according to their needs

end

Eligibility and priority for assignment of interim housing under project Roomkey are determined by "high-risk profile for COVID-19" [12]. According to LAHSA, high-risk is defined or determined by **age, chronic health condition, COVID-19 asymptomatic condition, persons currently staying in congregate facilities**. A priority list is generated from the above criteria[12].

The immediate red flag from this algorithm is that preferences and assignments are restricted by locality from the fact that the m housing options are distributed among local homeless service providers. Better options according to one's preferences could exist through another local service provider but they would never be available to this individual. We will do a deeper analysis of the above algorithm (check for Pareto optimality and strategy proofness) next.

3.4.3 Pareto Optimality

As evidence for why algorithm 3 is Pareto optimal, we showed two examples where the algorithm always finds an assignment that can not be improved without making any agent worse off, we then prompted the reader to find an example that proves otherwise. Here we will show an example in which algorithm 3 dominates LAHSA's algorithm 4. This is sufficient to prove that algorithm 4 is not Pareto optimal.

Example: Two homeless service providers

We will assume that the LAHSA has two local homeless service providers in different localities under the project Roomkey. Homeless service provider, P has housing options, a, b, c available. While homeless service provider, Q has housing options, x, z. We additionally assume an eligible person i seeking a housing option with the following preference list generated from their needs:

$$i : z \succ b \succ c \succ x$$

Under algorithm 4, we have two possible outcomes that depend on whether the LAHSA sends i to P or Q.

- If P, then i will most likely be assigned housing option b
- And if Q, then i probably gets their most preferred option z

Observe that because of locality, i could be assigned to an option that does not best fit their needs. This means that there exist cases where algorithm 2 can be dominated by another algorithm that can guarantee a better housing option to i.

One such algorithm is algorithm 1 where we would have all the available housing options a, b, c, x, z in one database. We would then assign i their most preferred housing option z. Algorithm 1 clearly Pareto dominates algorithm 2 in this example. As a counter-example, one could ask, what if there was another person j in the locality of Q that also preferred Z? Assigning z to i would sure leave j worse off. Let us set up this example and see why this is not a valid counter-example.

Example: Two homeless service providers and two eligible persons

We will assume that the LAHSA has two homeless service providers in different localities under the project Roomkey. Homeless service provider, P has housing options, a, b, c available. While homeless service provider, Q has housing options, x, z. We additionally assume two eligible persons i and j seeking housing with the following preference list generated from their needs:

$$i : z \succ b \succ c \succ x \tag{3.14}$$

$$j : z \succ a \succ c \succ b \tag{3.15}$$

Under algorithm 2, we assume that LAHSA sends both to the homeless service provider of their respective locality, that is, i to P and j to Q, j would then be assigned their most preferred option z but i would get b. However, if i has higher priority, then we see that algorithm 2 would never properly honor that priority while algorithm 1 would rightfully assign z to i and a to j which are their best possible outcome given a descending priority ordering of $i - j$.

3.4.4 Strategy Proofness

Example 4.3.2 demonstrates that it would be possible for someone to get a better housing option by simply misreporting their locality to LAHSA. We present that example again here, with a few changes, as proof that algorithm 2 is not strategy-proof.

Example: Two homeless service providers and two eligible persons revisited

We will assume that the LAHSA has two homeless service providers in different localities under the project Roomkey. Homeless service provider, P has housing options, a, b, c available. While homeless service provider, Q has housing options, x, z. We additionally assume two eligible persons i and j in the localities of P and Q respectively, seeking housing with the following preference list generated from their needs:

$$i : a \succ z \succ c \succ x \tag{3.16}$$

$$j : a \succ x \succ c \succ b \tag{3.17}$$

Under algorithm 2, If j misreported their locality, they would have a shot at getting their most preferred option a, but if the priority queue of $i - j$ is followed, they would end up with x.

Observe that under algorithm 1, it would not matter if j misreports or not, they would get option x either way while i will always get option a (which would be their rightful assignments according to the priority queue).

This simple example shows us that, indeed, persons can improve their chances by misreporting their preferences and locality in algorithm 2, which could leave them worse off whereas algorithm 1 protects against such incidents.

3.4.5 Locality Expansion

Locality is a key component in the comparison of our matching scheme to that employed by project Roomkey. And by locality, we mean the area considered when assigning housing options to new persons. If $U(p)$ is the expected utility for an individual k for an allocation from the m housing options, with a utility $u(x_i)$ and probability p_i for each housing option, we get the following definition.

$$U(p) = \sum_{i=1}^{m} u(x_i)p_i$$

It is easy to see that the expected utility for any individual i is nondecreasing with an increase in the size of the locality or the number of housing providers as long as all the utilities are nonnegative.

3.5 Conclusion

3.5.1 Discussion

Like past matching mechanism solutions to social problems, this mechanism promises to solve an age-old, complex problem more efficiently. With a Pareto optimal algorithm, we have confidence that this solution would be fair and consequentially improve social welfare without being susceptible to unfair strategies from those trying to cheat their way in.

Automating the assignment of housing options, which is currently done one-on-one by local service providers, should help reduce the amount of personnel required by undertakings like LA county's project Roomkey that cited a lack of sufficient personnel as a hindrance to its success. Besides personnel, we speculate that automation would also render other parts of the current system obsolete therefore resulting in a reduction of cost. This, too, would tackle another hindrance cited by LA county, that is, a lack of sufficient funding. Both these advantages come in addition to faster and more fitting assignments for all categories of unhoused persons including those left out (like the disabled with project Roomkey) by current assignment procedures.

Of course the matching algorithm alone can not fix homelessness and has to be supplemented by already-existing programs for job placement, drug addiction rehabilitation, domestic violence prevention, and recovery programs, health care provision, among others. We do not propose this mechanism as an overhauling solution but rather as a more efficient piece to be plugged into the vast effort to end homelessness.

3.5.2 Future work

We hope to obtain the support of many policy-makers and homeless service providers from different cities, support in the form of homelessness data, for example, data from the recent project Roomkey effort, and a clear outline of the current housing assignment procedure. This would allow for numerical investigation on the effectiveness of this matching mechanism on real-world data. We also intend to go beyond research and actually work with the same city policymakers and homeless service providers in implementing this algorithm in the field. In particular, we are seeking a collaboration with LA county to make this matching mechanism a part of future project Roomkey and Homekey efforts.

Chapter 4

A Matching Mechanism with anticipatory tolls for transport congestion pricing

This chapter presents a matching mechanism for assigning drivers to routes where the drivers pay a toll for the marginal delay they impose on other drivers. The simple matching mechanism is derived from the deterministic algorithm for online bipartite matching proposed in [14]. The toll, which is anticipatory in design, is an adaption of one proposed in [34]. Our research proves that the matching mechanism proposed here is Pareto user-optimal, that is, it is fair to all drivers and achieves a competitive ratio of $1 + log(m)$, where m is the number of available routes, when applied with a goal of minimizing total network travel cost.

4.1 Introduction

To some, taxing vehicle operators for road access seems unfair because it is clearly a regressive tax. However, it is highly logical because in addition to reducing road use, it could provide funds for improving roads and extending both the reach and convenience of transit services which should directly benefit less affluent travelers. A deeper look reveals that congestion pricing and related market mechanisms pose very complex economic problems. That is, establishing where in the networks to impose prices and what prices to pick to give road users incentives to limit their non-essential trips while also making essential road use available for middle and low income users.

Many economists have tried to put realistic numbers on the cost of congestion in terms of time lost in traffic and fuel wasted, but the true costs are much higher because of road injuries to drivers, cyclists and pedestrians and the short-term and long term enormous environmental impacts [9].

Despite the emergence of new Mobility-as-a-Service (MaaS) modes in the past decade [71], both the number of private car owners and overall vehicle miles traveled (VMT) steadily increases every year [91]. In fact, in most urban areas MaaS has increased VMT without decreasing car ownership because these services have drawn transit users out of those systems and increased the fraction of single occupancy vehicles around airports and other major attractions. Without new road pricing solutions we can confidently predict that road congestion will soon become the leading cause of air pollution and road accidents.

In this chapter we propose the design of a market matching mechanism for assigning drivers to travel routes in which space on congested routes is allocated to drivers willing to pay a fee which is equal to the cost of the delay imposed on other drivers. We show that our proposed matching mechanism is pareto user-optimal, strategy-proof and, from past literature, we know that it achieves a competitive ratio of $1 + log(m)$ where m is the number of possible routes between the origin-destination pair in consideration. While we present this model from the point of view of the computer science literature on matching markets, we argue that such a system could be implemented in practice due to recent advances in short-term traffic estimation techniques [11, 29, 24], as well as advances in dynamic tolling systems and autonomous vehicles.

4.1.1 Relevant Literature Review

This chapter contributes to a well established large body of work on congestion pricing, online matching for resource allocation, and the future of transportation given the increasing adoption of MaaS and autonomous cars. Below we review a few key papers in the above mentioned research topics.

Congestion Pricing literature

The idea to use a monetary toll as a tax on the negative consequences of road usage first appeared in the literature in 1920 [99]. Since then, many scholars have proposed different variations of fixed and dynamic tolls as tools to curb congestion. The intuition being that a properly set toll would give drivers an incentive to minimize unessential travel during times of high road use demand. [30] provides an extensive survey of the methodologies employed for congestion pricing. The primary types of tolls are: facility based tolls where a specific infrastructure is taxed, area-based tolls that are commonly implemented as cordon where drivers pay to enter or exit, zone based tolls, distance and time-varying tolls, all of which can be fixed or dynamic.

Because this chapter employs a dynamic toll, we also want to highlight [125] which introduces two approaches to dynamic tolls; the first approach adjusts the toll rate based on the concept of the feedback control, while the second approach would 'learn' in a sequential fashion motorists' willingness to pay and then determine pricing strategies to explicitly achieve the operating objectives. Additionally, [72] proposes the use of a dual variable approximation based heuristic combined with the Method of Successive Averages (MSA) to determine time-varying tolls in networks. This chapter does not argue against the efficiency of the tolls proposed in those papers, but chooses to employ (with minor modification) the anticipatory toll introduced in [34] on the basis of simplicity in implementation.

Simplicity and fairness of a congestion pricing scheme are key factors in influencing how easily a scheme is accepted by our socio-economic societies. These factors and more are explored in [106] and [55] which examine proposed and implemented congestion pricing case studies.

Our work comes at such a relevant time where the costs of congestion are evident to all of society and the benefits of congestion pricing are also very evident as shown by many scholars. [8] uses a spatially detailed general equilibrium model of the Los Angeles region to deliver an economic analysis of congestion pricing which shows both the economic cost of congestion and the economic benefits of congestion pricing. [23] shows that congestion pricing has reduced the volume of nonessential commutes in Melborn by 30%. [114] provides evidence of reductions in accidents and air quality improvements in London, before focusing increases property values inside the congestion charging zone. [15] examines the positive change that the area-based toll in New York City's central business district could have on emission levels.

We refer readers to [30] and [26] for a more complete presentation of congestion pricing methodologies and technologies.

Online matching for dynamic resource allocation

Since [67]'s proposal of the RANKING algorithm for online bipartite matching that achieves a competitive ratio of $1 - \frac{1}{e}$, a result that [17] shows to be asymptotically optimal for any randomized online bipartite matching algorithm. Many other scholars have applied matching algorithms towards online resource allocation. We will review two relevant applications and direct the reader to [79] for a more thorough examination of online matching in it's different forms. [126] applies a greedy algorithm towards the online weighted matching problem of allocating passengers to drivers in a ride sharing systems and [33] uses an linear programming algorithm to solve the online resource allocation problem with offline reusable resources wherein they achieve a competitive ratio of $\frac{1}{2} - \epsilon$ for any $\epsilon > 0$. Quick examination will reveal that our problem structure is quite similar to the problems shown in both these papers.

Mechanism design for Congestion pricing literature

This chapter's contribution was inspired by the recent work of [58] where the congestion pricing problem is modeled as a auction design problem. With this model, "a mechanism designer can design mechanisms involving pricing schemes and allocations to implement efficient road usage."[58] This chapter also exploits this technique of using a mechanism that simultaneously allocates drivers to routes and also sets a toll to mitigate congestion but with the goal of fairness in assigning routes to every driver. We also assume that the drivers want an instantaneous assignment which a bidding scheme would not fulfill. Additionally, a bidding scheme would be unfairly baised because drivers of higher economic class would simply bid higher than low income earners. Xiao and Zhang shows the advantages of employing a multiclass pareto-improving pricing mechanism that takes into account a difference in VOTs of drivers in different economic classes. Our work is most similar to [19] that suggests a mechanism to assign heterogeneous drivers to routes in a congestion-free network with a public transit option. Drivers are assigned to travel on routes that best meet their time preferences with the assumption that current traffic conditions will hold. We, however, do not assume that the drivers are willing to take public transit or that the network is congestion-free or that current traffic conditions will hold. Similarly, as a solution to congestion caused by truck traffic, [95] proposes two ”pricing-and-routing” schemes that they prove to be pareto-improving and strategy proof. We differ from some other researchers in that rather than explicitly considering drivers' individual value-of-time (VOT), we use willingness to pay tolls rather than selecting toll-free routes as a proxy for VOT and in using both time and cost preferences in assigning drivers to routes that maximize their utility. In this approach we differ from [10], [117] and many other researchers. Our work also draws on earlier work in [16] which considers congestion pricing with an untolled alternative.

4.1.2 Summary of Contributions

We start off with a model for the route assignment problem under traffic congestion conditions in section 4.2 , complete with a problem formulation and summary of the proposed algorithm. Where [58] uses an auction mechanism, we propose the employment of a matching mechanism with an anticipatory toll as an algorithmic solution in section 4.3. The simple matching mechanism proposed here is derived from the deterministic algorithm for online bipartite matching proposed by [14]. The toll, which is anticipatory in design, is an adaption of one proposed by [34]. The text goes on to prove that the matching mechanism proposed here is pareto user-optimal as defined by [118], strategy-proof as defined by [85], and can be adapted to give network optimal results for minimizing total social cost of travel. In section 4.4, we compare this matching with the auction mechanism when both are applied towards traffic congestion pricing. A discussion follows in section 4.5.

4.2 Model

In this section, we present a problem definition, complete with theory of how the anticipatory toll is obtained, and a summary of the matching mechanism employed. As a prelude, the notation used is listed below.

Table 4.1: Table of Notation

r	$\triangleq$	Route r
d	$\triangleq$	Driver d
q	$\triangleq$	Timestep
k_f	$\triangleq$	Route threshold capacity for free flowing traffic
k_t	$\triangleq$	Route capacity at a time t
E_t	$\triangleq$	Estimated travel time at a specific time t
E_f	$\triangleq$	Estimated travel time with free flowing traffic
C_r	$\triangleq$	Toll on route r
C_d	$\triangleq$	Toll paid by driver i
X_t	$\triangleq$	Traffic concentration/flow at time t
A,B,F β	$\triangleq$	Congestion constants
α_d	$\triangleq$	Driver d's willingness to pay toll (equivalent to Value of Time)
$R(E,C)_r$	$\triangleq$	Route r's cost function
$U(E,C)_d$	$\triangleq$	Driver d's utility function
P	$\triangleq$	Penalty charge

4.2.1 Problem Formulation

Consider a metropolis where n drivers want to travel from a common origin O to a common destination D, with m routes available to the drivers. Note that a typical city will have many such O-D pairs, for example residential-work area pairs from which most travelers leave at common times.

Define a route r to have;

- Threshold Capacity, k_f, which is the route capacity that allows for free flowing traffic.
- A cost function, $R(E, C)_r = (E_t - E_f)C_r$

Additionally, Define a driver d to have;

- A Willingness-to-pay measure (Value of time), α_d, a maximum toll the driver is willing to pay, with the assumption that all drivers prefer the fastest routes.
- A utility function, $U(E, C)_d = (E_f - E_t)C_d$, where;
  - $E_t = E_f[1 + A(\frac{k_t}{k_f})^B]$ As presented by [22].
  - $C_r^t = C_r^{t-1} + \beta(X_{t+q} - X_t)$ As presented by [34].

Ideally, we would like to dynamically match drivers to routes in some way such that every driver d's utility is maximized and while also minimizing total congestion cost for all routes.

Here, we propose a simple online matching algorithm;

With a deadline to the assignment, drivers have an option to opt out of travel, however, if they use a route that is different from the assigned route, they incur a penalty; $P = C_r^t + F$, where F is a fixed rate. Analysis in later sections will show that this simple matching mechanism is

Algorithm 5: Online Driver-Route Matching

for *Each driver that arrives online* **do**

1. Rank all routes available to driver d by the projected utility $U(E, C)_d$
2. Assign top ranked route to driver d with a deadline to accept the assignment

end

Pareto user-optimal and with minor algorithm changes, also minimizes the total congestion cost to within a competitive ratio of $1 + log(m)$. We will also show that prove that the matching is strategy-proof.

4.2.2 Anticipatory Toll

The cost of congestion on a route r is distributed among all travelling drivers in the form of an anticipatory toll that is calculated from future traffic conditions. Below, we provide a definition.

$$C_r^t = C_r^{t-1} + \beta(X_{t+q} - X_t)$$

The driver is then charged as follows;

$$C_d^t = \begin{cases} \frac{C_r^t}{k_t}; \quad if \;\; k_t - k_f > 0 \\ 0; \quad otherwise \end{cases} \tag{4.1}$$

[34] compare the effectiveness of a static toll, reactive toll, and an anticipatory toll. Their findings show that the anticipatory toll provides the best throughput.

Calculating Future traffic flow (X_{t+q})

We propose the use of convolution-long short term models (CNN-LSTM) to predict short term traffic flow. Our team members at the University of California, Asadi and Regan [11] provide such a model which takes an input a vector $X = X_0, X_1, ..., X_t$ of traffic flow conditions up until time t, then provides as output, traffic flow prediction at time $t + q$. We refer the reader to [11] for more detail.

4.3 Matching Mechanism

Traffic congestion is a socioeconomic problem therefore any solution for congestion pricing has to be evaluated by how efficient it is from the perspective of road users and society as a whole. With that in mind, this section provides a proof that the matching algorithm proposed by this text is indeed pareto user-optimal and also achieves a fraction of the optimal total route network cost. We begin with an illustrative example of the algorithm.

4.3.1 Illustrative Example

Given a collection of n drivers in the order in which they arrive online, $D = (d_1, d_2, ..., d_{n-1}, d_n)$ and m available routes, $R = (r_1, r_2, ..., r_{m-1}, r_m)$ For each driver d_i;

1. Rank all the routes such that, $U(E_{r_i}, C_{r_i})_{d_i} \geq U(E_{r_{i+1}}, C_{r_{i+1}})_{d_i}$, where $U(E_{r_i}, C_{r_i})_{d_i}$ is the utility driver d_i would get from taking route r_i. Ties are broken by route capacities, k_t.

2. Assign the top ranked route with a deadline within which the driver must begin their travel.

While it is intuitively clear that this user-optimal, a short proof is provided below for completeness.

4.3.2 Pareto Optimality

Remember that an allocation is Pareto Optimal if there is no alternate allocation in which an individual is better off and no other individual is worse off.

Theorem 4.1. *The allocation from the simple algorithm 5 is Pareto optimal, that is, it is not Pareto dominated by any other allocation.*

Proof. Let us assume that μ is the allocation achieved from running the algorithm 5 described in section 2. Also assume that μ is not Pareto optimal, which would mean that there exists an allocation μ' that Pareto dominates μ, where this μ' is generated by a different algorithm that assigns routes using a different criteria from the top ranked route according to expected utilities of the available routes. This means that some driver d was a assigned a route in μ' different from his top ranked route in μ. This presents a contradiction because the assignment in μ should achieve the best possible utility given the highest toll that d is willing to pay, and the expected travel time for every route available at the time of assignment. A different assignment would not get d a better utility and having that assignment in μ' means that μ' can not Pareto dominate μ. Therefore as long as μ assigns every driver the route that achieves the best possible utility at the time of assignment, the conditions for Pareto Optimality should be satisfied. $\square$

4.3.3 StrategyProofness

For this matching, the driver is required to report the maximum toll they are willing to pay and get online when they are ready to travel. Lets consider two cases for the proof.

Case 1: Driver requests a route before they are ready to travel

In this scenario, we have a driver d requests a route earlier that he is able to travel so as to be higher in the driver queue. If a route is assigned and the driver does not start traveling before the deadline, the assignment will be terminated, in which case the driver gets $U_d = 0$. The only way they can get maximum possible utility is if they request a route when they are ready to travel.

Case 2: Driver under reports the maximum toll they are willing to pay

Lets also consider a driver, d that reports their maximum toll to be l but they are actually willing to pay a higher toll h. If $C_d \leq l < h$:

$$U(E, C)_d = (E_f - E_t)C_d \geq (E_f - E_t)l > (E_f - E_t)h$$

However, If $l < C_d \leq h$, then the driver is not assigned a route because we assume they are not willing to pay a toll higher than their reported maximum, l. This cannot be beneficial to a driver that truly wishes to travel.

Further, we make the assumption that reporting a higher maximum would be individually irrational because the driver would be assigned routes whose tolls they cannot or will not pay. Therefore we do not explicitly include this as a separate case.

4.3.4 Network Optimality: matching for social good

As earlier stated maximizing users' utility is our primary goal. However, the matching mechanism proposed here can easily be adjusted to control the negative social costs of traffic congestion. If a user-optimal assignment is one in which every user gets the best possible assignment they can get by any matching, a network optimal asks whether the total cost for all routes is minimized. For the network optimality result, we will begin with a simple reduction of the traffic assignment problem to online bipartite matching.

Consider a graph $G = (U, V, E)$(fig. 1), where the vertices in $|U| = n$ are the drivers arriving online and the vertices in $|V| = m$ are routes. Every vertex $u \in U$ has an edge cost z_i and the total cost on v, $R_v = \sum_{neighbor(v)} z_i$, the sum of all the costs of the adjacent neighbors of v. We want to assign every u to some v such that the total cost of the route network is minimized.

Algorithm 6: Online Driver-Route Matching

for *Each driver who requests a route* **do**

1. Rank all routes available to driver d by their current cost R_r
2. Assign top ranked route to driver d

end

It can be proved that this concise deterministic matching mechanism achieves a competitive ratio of $1 + log(m)$. The reader is directed to [14] for a complete proof.

4.4 Comparison to Auction Mechanism

This section compares our matching mechanism to an auction mechanism proposed by Heller et al. for congestion pricing.[58] presents a two driver example to illustrate their mechanism, we will show how the matching mechanism proposed here performs on the same scenario.

4.4.1 Auction mechanism

Under the auction mechanism (AUC), we have the same scenario of n drivers traveling from origin, O to destination, D. For simplicity, but without loss of generality, we assume a single route between O and D that may or may not be congested (as is assumed in [58], where the auction mechanism for congestion pricing is introduced). Every driver d_i has a value of time (VOT) (θ_i) where $(\theta_i) > 0$. The VOT for each driver can also be time-varying. Every driver's VOT is unknown to the mechanism designer, and drivers can travel(T) or opt out(O). Under the AUC, drivers can reduce travel time by bidding higher prices which would result in fewer drivers travelling. Under this mechanism, drivers place their bids according to their VOT and an allocation rule $A(x)$ determines which drivers get to travel, with those drivers paying a price determined by a payment rule $P(x)$.

[58] defines the utility of driver i opting out to be

$$u_i^o = 0 \tag{4.2}$$

and traveling with VOT θ, number of drivers k, and paying p_i, to be

$$u_i^T = v(\theta, k) - p_i, \tag{4.3}$$

where $v(\theta, k)$ is the value gained from the trip. This value can be gotten from $v(\theta, k) = \theta(t_f - t_k)$, where S is time without traffic and $c(k)$ is the time with congestion.

4.4.2 The two driver example

Consider a scenario where we have two drivers that wish to travel with VOT (θ_1, θ_2). We compare the outcomes when using an auction (AUC) versus those when using the matching discussed earlier (MAT). Below is a case by case comparison following the three cases presented in [58]'s two drivers example. Here $M = (i, j)$ represent whether got a travel/no travel allocation. $i = 1$ means driver 1 gets a route while $i = 0$ means driver 1 does not get a route to travel.

1. case 1: $\theta_1 \in [\frac{1}{2}\theta_2, 2\theta_2]$
   (a) Allocations
   $$M^{AUC} = (1,1) \qquad\qquad M^{MAT} = (1,1)$$
   (b) Payments
   $$P_1^{AUC} = \theta_2 \qquad\qquad P_1^{MAT} = C_d = \frac{i}{j}\theta_1 = \frac{i}{j}[\frac{1}{2}\theta_2, 2\theta_2]$$
2. case 2: $[\theta_1 > 2\theta_2]$
   (a) Allocations
   $$M^{AUC} = (1,0) \qquad\qquad M^{MAT} = (1,1)$$
   (b) Payments
   $$P_1^{AUC} = 3\theta_2 \qquad\qquad P_1^{MAT} = \frac{i}{j}\theta_1$$
3. case 3: $[\theta_1 < \frac{1}{2}\theta_2]$
   (a) Allocations
   $$M^{AUC} = (0,1) \qquad\qquad M^{MAT} = (1,1)$$

(b) Payments

$$P_1^{AUC} = 0 \qquad\qquad P_1^{MAT} = \frac{i}{j}\theta_1$$

4.4.3 Utilities

Under some mild assumptions, we show here that the utilities achieved by the matching are superior to those achieved by the auction mechanism.

Utility under Auction

$$U_d = \theta_d(t_f - k_c),$$

[58] assumes that,

$$t_c \equiv k_c, t_f = 4$$

therefore

$$U_d = \theta_d(4 - t_c)$$

Utility under Matching

$$U_d = (t_f - t_c)C_d$$

and

$$C_d = \frac{i}{j}\theta_d$$

with

$$i < j, t_f = 4$$

then

$$C_d \leq \theta_d$$

and therefore

$$U_d = (4 - t_c)\frac{i}{j}\theta_d$$

From above, we can see that the possible utility obtained from the auction mechanism by a driver, d in the two driver example, is a fraction of the possible utility obtained under the matching mechanism, i.e;

$$U_d^{MAT} = \frac{i}{j}U_d^{AUC}$$

Assuming we have congested routes($t_f < t_c$), we can therefore conclude that the matching mechanism is preferable for each user since it achieves a higher payoff for the drivers,

$$U_d^{AUC} \leq U_d^{MAT}$$

4.5 Discussion

4.5.1 Implications

As Infrastructure-as-a Service, Platform-as-a Service and Software-as-a-Service become the dominant computing models for businesses large and small, Mobility-as-a-Service is emerging as an important, and in the future, possible dominant model for transportation. While the potential benefits of shared use autonomous vehicles are being examined from every available angle, the negative impacts of early MaaS systems (ride-hailing services in particular) are wreaking havoc in cities and at already congested sites including airports and rail terminals. Therefore, even in the US where there has been extensive resistance to congestion based pricing, cities such as New York, Los Angeles and San Francisco are considering following the leads of London, Singapore and Stockholm in enacting congestion pricing and low emissions zone pricing to reduce peak period congestion and pollution. Further, advances in tracking technology and emerging secure and privacy preserving contracting systems make it possible to tax vehicles or drivers for the use of limited infrastructure without putting their personal travel data at risk.

While estimates of the date at which society will see wide-scale adoption of autonomous vehicles have been widely inaccurate, someday this will surely be the norm. Research into the impact of autonomous vehicles on total vehicle-kilometer-traveled (VKT) have come up with highly variable estimates [38], but what is assumed is that without road pricing that autonomous vehicles (many of the electric) would be free to impose externalities on the system paying only for fuel use. Therefore a matching mechanism such as ours would allocate scare resources more effectively.

4.5.2 Conclusion

This chapter presents a matching mechanism for assigning drivers to routes where the drivers pay a toll for the marginal delay they impose on other drivers. The toll, which is anticipatory in design, is an adaption of one proposed by [34]. Our research proves that the matching mechanism proposed here is pareto user-optimal and can be adapted to an algorithm that minimizes total social cost of travel with a competitive ratio of $1 + log(m)$.

In the future, we intend to use a neural network model to predict short term future traffic flow conditions such as the one proposed by [11] and charge a toll that reflects those future conditions. Another goal is examine how efficient this matching mechanism is for solving the dynamic traffic assignment problem and ideally a multi-class dynamic assignment problem with elastic demand such as the one examined recently by Wang et al [120]. We realize of course that applying these models to such a complex problem is an ambitious goal.

Chapter 5

Outro

5.1 Concluding Remarks

Matching mechanisms are and will continue to be valuable tools in the continuous digitization of social systems and infrastructures. Matching algorithms employed by for-profit platforms like Uber, Lyft, Airbnb, and plenty of others, have disrupted their respective markets. This dissertation has presented evidence that we can, as a society, continue to apply these highly versatile algorithms to towards more social problems as well. Chapter 2 and 3 showed that a central core redistribution is a more welfare-efficient algorithm when compared to local independent uncoordinated donations of surplus resources. We mathematically showed that an optimal allocation of the surplus that minimizes waste and maximizes social welfare is only possible with a core redistributor. This is further supported by two qualitative case studies in food surplus redistribution and welfare housing allocation.

Chapter 4 proves that online matching of drivers with a common origin and destination is Pareto user-optimal, that is, it is fair to all drivers and achieves a competitive ratio of $1 + log(m)$, where m is the number of available routes, when applied with a goal of minimizing total network travel cost. The proposed mechanism is also strategy-proof.

Below, we will close with a series of open problems from each of these areas explored in chapters 2,3, and 4.

5.2 Open Problems

5.2.1 Open Problems in Algorithm Waste Reduction

Individual rationality in the absence of government funding

Research question: *For any arbitrary donation center, would the cost of joining a network of donations centers, that run a core redistribution of surplus and cover the cost of redistribution, be less than the cost of seeking local independent donations out of network?*

This is the question of individual rationality specifically for donation centers in affleunt neighborhoods where donations may be in plenty. If we imagine the worst case scenario there is no funding from a government or third party donor to cover the cost of redistribution, would it still make sense for donation centers to merge resources and run the core redistribution because the cost of being in the core(in the network) would still be less than the cost of being out of the core (out of network). This is still an open and important question.

Since a core redistributor would guarantee minimal amount of waste at each donation center, the absence of a cost of waste management for each donation center could offset the new contribution to the cost of redistribution. Additionally, other benefits from a core redistribution like standardization of donations could also alleviate other operational costs for each donation center that would justify joining a network of donation centers. However a mathematical proof to show these cost offsets is required to properly answer this open question.

Capacity of a core redistribution network

Research question: *What is the geographical upper and lower limits and user capacity constraints required for a core redistribution to achieve the proven benefits over local independent donation mechanisms?*

Phillips et al. [98] gives some numerical bounds on the capacity constraints and geographical limits that have to be met for a core redistribution to become beneficial interms of cost of redistribution and waste created. To the best of our knowledge, theoretical proofs of these bounds have not been put forth anywhere in the literature. So questions like, how many localities can a core redistributor cover while still achieving minimal waste, and also meeting all the donation centers' demand?

The mechanism proposed in Chapter 2 had constraints to minimize waste while maximizing welfare, specifically satisfying demand. One could imagine applying the same mechanism and proof with an added constraint of minimizing costs of transportation. Intuitively, the transportation cost constraint could allow for effective redistribution over a large collection of localities. However it is not trivial to determine how that would affect waste and welfare, for example in a network with both dense and sparse localities. Theoretical or empirical investigation is required.

Strong preferences

Research question: *How would strong preference on the donations from donation centers affect the core redistribution?*

Consider the scenario where donation centers specifically prefer certain items over others. How these strong preferences would be met is not accounted for in Chapter 2. It therefore remains an open question how the existence of strong preferences would alter the core redistribution.

The modification for multiple bundles given in chapter 2 could be sufficient to cater for strong preferences as they would be reflected in the quantities demanded for each item from each donation center. However, while it seems intuitively the case, a proof is still required to show that a core redistribution would optimally meet every donation center's preferences on the items.

5.2.2 Open Problems in Matching Mechanism for Housing

Post-lockdown housing for the unhoused

Research question: *Given the end of covid lock downs and restriction around the world, how does the change in supply of zero to low income housing affect the matching mechanism proposed in Chapter 3?*

The matching of low income persons to housing options proposed in Chapter 3 relied on the existence of low income housing options like vacant hotel and motels that were in abundance during early covid lock downs. The end of covid restrictions means that some or even most of this supply is not available any more. Is the matching mechanism still plausible solution with a smaller supply of housing options? Is there new housing options, due to a post covid restriction market, to supplement pre-covid options?

The mechanism's Pareto optimality and strategy proof guarantee should be independent of the size of supply but perhaps a case study or numerical data to prove that this mechanism is still a plausible solution is required.

5.2.3 Open Problems in Matching Mechanism for transport

Network equilibrium

Research question: *Does the matching mechanism proposed for matching drivers to congested routes maximize the collective network utility?*

We should that the mechanism would maximize individual utilities for each driver in term of travel time and toll charged. However whether the same solution would ensure that all the collective utility to all drivers in the network is an open question. Certainly adding more drivers to congested routes would increase the collective time of travel, whether that time would still be minimal with a mechanism than without one or under a different mechanism is not clear.

The proof of this is not trivial. One may have to consider literature on dynamic traffic allocation and traffic network equilibrium before attempting a proof.

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