A Simplex-like Algorithm for Linear Fisher Markets

Bharat Adsul¹, Ch. Sobhan Babu², Jugal Garg¹**, Ruta Mehta¹, and Milind Sohoni¹

¹ Indian Institute of Technology, Bombay
adsul,jugal,ruta,sohoni@cse.iitb.ac.in
² Indian Institute of Technology, Hyderabad
sobhan@iith.ac.in

Abstract. We propose a new convex optimization formulation for the Fisher market problem with linear utilities. Like the Eisenberg-Gale formulation, the set of feasible points is a polyhedral convex set while the cost function is non-linear; however, unlike that, the optimum is always attained at a vertex of this polytope. The convex cost function depends only on the initial endowments of the buyers. This formulation yields an easy simplex-like algorithm which is provably strongly polynomial for many special cases. The algorithm can also be interpreted as a complementary pivot algorithm resembling the classical Lemke-Howson algorithm for computing Nash equilibrium of two person bimatrix games.

Keywords. Market Equilibrium, Convex Optimization.

1 Introduction

Fisher [2] and Arrow-Debreu [3] market models are the two fundamental market models in mathematical economics. In this paper, we focus on the Fisher market model with linear utilities. An instance of this model consists of a set of buyers, each with money endowment and (linear) utility functions, and a set of divisible goods. The problem is to determine market equilibrium prices and allocation of the goods to buyers such that the market clears and each buyer gets her utility maximizing bundle subject to her budget constraints. Towards this, Eisenberg and Gale [4,5] formulated a remarkable convex optimization program whose optimal solution, more precisely, values of the primal and dual variables at an optimal solution, captures equilibrium allocation and prices respectively.

Many algorithmic results [6-10] pertaining to the computation of market equilibrium prices and allocation for the linear case of Fisher and Arrow-Debreu market models have been obtained. Deng et al. [6] gave a strongly polynomial time algorithm for the Fisher market with either constant number of goods or constant number of buyers. Building on the Eisenberg-Gale program, Devanur et al. [7] developed a primal-dual type polynomial time algorithm to solve the Fisher market model. For the more general Arrow-Debreu market, Eaves [10] gave a Linear Complementarity Problem (LCP) formulation and showed that the Lemke’s algorithm [11], when applied to this LCP, converges to a market equilibrium. Later, Jain [8] obtained a polynomial time algorithm for Arrow-Debreu market. More recently, Orlin [9] obtained a strongly polynomial time algorithm for the Fisher market. A tantalizing open question is to formulate a linear program that captures the Fisher solution. A positive resolution of this question would, of course, imply a simplex-like algorithm for computing the same. This paper is an attempt towards this objective.

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** Corresponding Author
This paper is the first in the series of papers on vertex marching algorithms for market equilibrium computation. All of them are complementary pivot algorithms resembling either Lemke or Lemke-Howson algorithm. The Lemke’s scheme can be applied to any LCP, however with no convergence guarantees. The Lemke-Howson \cite{12} (LH) scheme was known only for computing a Nash equilibrium for two person bimatrix games (2-Nash). Both Lemke and Lemke-Howson are complementary pivot schemes, but work in two different polytopes and possibly lead to different insights. Lemke’s scheme expands the LCP polytope by going one dimension up; follows a path on its 1-skeleton and stops whenever it hits the original LCP polytope (a section in the expanded polytope). In contrast, LH scheme works on the LCP polytope itself; follows a path on its 1-skeleton and stops when it hits a solution vertex. None of these schemes require monotonicity based argument for convergence.

In this paper, we propose a novel convex optimization formulation for the Fisher market problem. In the Eisenberg-Gale formulation \cite{6,5}, the set of feasible points is a convex polytope which merely models the packing constraints and is oblivious to the parameters of the problem. Like the Eisenberg-Gale formulation, the set of feasible points in our formulation is also a convex polytope. However, unlike that, our convex polytope is defined in terms of the input parameters, specifically utilities and money, and is rich enough so as to ensure that the optimum is always attained at a vertex of this polytope. Furthermore, the convex cost function in our formulation depends only on the initial endowments of the buyers. There is another formulation, which maximizes a convex function under flow constraints, obtained by Shmyrev \cite{13} and Birnbaum et al. \cite{14}, however this formulation also does not guarantee the optimum to be at a vertex.

We notice that the optimum vertex satisfies a set of complementarity conditions. Using these conditions, we define special vertices in our polytope and every such vertex corresponds to the Fisher solution with a different endowment vector. Next, we give a combinatorial characterization of special vertices and show that starting from any special vertex, there is a simplex-like path of special vertices where the cost function monotonically increases and it ends at a vertex corresponding to the Fisher solution. There may be many such paths of special vertices in the polytope. Using a simple pivoting rule, we give an algorithm, which traces one such path. Since all the vertices on the path followed by the algorithm satisfies all the complementarity conditions, the pivot in each step is complementary pivot, and it resembles Lemke-Howson algorithm because the polytope is unchanged. The primary difference from Lemke-Howson is the monotonicity based argument for convergence, which is why it is also simplex-like. Experiments indicate that our algorithm is practical – on randomly generated instances, the number of iterations it needs is linear in the total number of non-zero utilities specified in the input. Further, we show that this algorithm is strongly polynomial for many special cases. Two interesting cases are:

- Either the number of buyers or the goods is fixed.
- All the non-zero utilities are of the type $\alpha^k$, where $\alpha > 0$ and $0 \leq k \leq M$ (M is bounded by a polynomial in the number of buyers and goods).

This algorithm is conceptually simple, much easier to implement and runs very fast in practice. In fact, these special cases seem sufficient to handle most practical situations. This is because, firstly, in practice, utilities are hardly exactly known, and secondly, as shown in \cite{15} buyers have every reason to strategize and report fictitious utilities. The events that may occur in the algorithm, while finding the adjacent special vertex, are similar as in the DPSV algorithm \cite{7}, however one crucial difference is that the prices, DPSV algorithm computes at intermediate stages, may not occur at a vertex in the polytope. The DPSV algorithm may be interpreted as an interior point method in our formulation. Further, the utility of our formulation is also illustrated by its easy extension to incorporate transportation costs as well (see Appendix A). There seems no way to modify Eisenberg-Gale or Shmyrev formulations to capture the equilibrium solution for this extended model. Independently, Chakraborty et al. \cite{16} also
give a similar formulation for this extended model along with an algorithm to compute \(\epsilon\)-approximate equilibrium prices and allocations. However, the Fisher market with transportation cost may have irrational solutions, so the optimum solution may not be at a vertex.

In a follow-up work \[17\] we consider an LCP-like formulation, using the complementarity conditions of this paper, for Arrow-Debreu model with linear utilities, and give a Lemke-Howson type algorithm on utility space while market clearing is always enforced. The algorithm starts with an easy to handle utilities and moves continuously to the original utilities, while keeping track of the solutions for the intermediate utilities. In this process it keeps expanding the polytope, and again convergence is proved using monotonicity based argument. An adaptation of this algorithm to scaling gives an efficient algorithm for Fisher markets. After this, we consider Arrow-Debreu markets with more general utility function of separable piecewise-linear concave (SPLC), for which it was known that equilibria are rational but computing one is PPAD-complete \[18\], a complexity class defined by Papadimitriou \[19\]. After failed attempts of extending our previous algorithms we considered Eaves \[10\] algorithm for the linear case. His LCP formulation and our LCP-like formulation, for capturing market equilibria for the linear case, turned out to be similar. In \[20\] we extended Eaves’ formulation to capture market equilibrium for the SPLC case, and proved that Lemke’s algorithm when applied to this LCP converges to an equilibrium.

**Organization.** The rest of the paper is organized as follows. In Section \[2\] we give a precise formulation of the Fisher market problem and introduce the new convex optimization program and analyze it. In Section \[3\] we discuss the simplex-like algorithm. In Section \[4\] we show that the algorithm is provably strongly polynomial for many special cases. Section \[5\] summarizes the experimental results on randomly generated instances. Finally we conclude in Section \[6\].

## 2 New Convex Optimization Formulation

We begin with a precise description of the Fisher market model.

### 2.1 Problem Formulation

The input to the Fisher market problem is a set of buyers \(B\), a set of goods \(G\), a utility matrix \(U = [u_{ij}]_{i \in B, j \in G}\), a quantity vector \(q = (q_j)_{j \in G}\) and a money vector \(m = (m_i)_{i \in B}\), where \(u_{ij}\) is the utility derived by buyer \(i\) from a unit amount of good \(j\), \(q_j\) is the quantity of good \(j\), and \(m_i\) is the money possessed by buyer \(i\). Let \(|B| = m\) and \(|G| = n\). We assume that for every good \(j\), there is a buyer \(i\) such that \(u_{ij} > 0\) and for every buyer \(i\), there is a good \(j\) such that \(u_{ij} > 0\), otherwise we may discard those goods and buyers from the market.

The problem is to compute equilibrium prices \(p = [p_j]_{j \in G}\) and allocations \(X = [x_{ij}]_{i \in B, j \in G}\) such that they satisfy the following two constraints:

- **Market Clearing:** The demand equals the supply of each good, *i.e.*, \(\forall j \in G\), \(\sum_{i \in B} x_{ij} = q_j\) and \(\forall i \in B\), \(\sum_{j \in G} p_j x_{ij} = m_i\).
- **Optimal Goods:** Every buyer buys only those goods, which give her the maximum utility per unit of money (*bang per buck*), *i.e.*, if \(x_{ij} > 0\) then \(\frac{u_{ij}}{p_j} = \max_{k \in G} \frac{u_{ik}}{p_k}\).

Note that, by scaling \(u_{ij}\)’s appropriately, we may assume that \(q\)’s are unit.
2.2 Convex Program

In this section, we introduce the new convex optimization program whose optimal solution captures the Fisher market equilibrium. Our convex program is described in Table 1, where $p_j$ corresponds to the price of good $j$ and $z_{ij}$ corresponds to the money spent by buyer $i$ on good $j$. At optimum, $\frac{1}{y_i}$ is the bang per buck of buyer $i$. We refer to the ambient space as the $y$-$p$-$z$-space.

<table>
<thead>
<tr>
<th>Table 1. New Convex Program</th>
</tr>
</thead>
<tbody>
<tr>
<td>maximize $\sum_{i \in B} m_i \log y_i$</td>
</tr>
<tr>
<td>subject to $\forall i \in B, \forall j \in G : u_{ij} y_i \leq p_j$</td>
</tr>
<tr>
<td>$\sum_{j \in G} p_j \leq \sum_{i \in B} m_i$</td>
</tr>
<tr>
<td>$\forall i \in B : y_i \geq 0$</td>
</tr>
<tr>
<td>$\forall j \in G : p_j \geq 0$</td>
</tr>
<tr>
<td>$\forall i \in B : \sum_{j \in G} z_{ij} \leq m_i$</td>
</tr>
<tr>
<td>$\forall j \in G : \sum_{i \in B} z_{ij} = p_j$</td>
</tr>
<tr>
<td>$\forall i \in B, \forall j \in G : z_{ij} \geq 0$</td>
</tr>
</tbody>
</table>

Note that the feasible set $O$ is a convex polytope in $y$-$p$-$z$-space and the cost function is independent of the variables $z_{ij}$. Let $O_{aux}$ be the auxiliary polytope in the $y$-$p$-space defined by the constraints 1 to 4 and the related convex program (with the same cost function) be the auxiliary convex program.

Claim. $Pr(O) = O_{aux}$, where $Pr(O)$ is the projection of $O$ onto the $y$-$p$-space.

Proof. Clearly, $Pr(O) \subseteq O_{aux}$, and for $O_{aux} \subseteq Pr(O)$, $Z = [z_{ij}]$ should be constructed for a given $(y, p) \in O_{aux}$. One way to do this is by constructing a max-flow network, where there is an edge from the source to every good $j \in G$ with capacity $p_j$ and from every buyer $i \in B$ to the sink with capacity $m_i$. Further, there is an edge from every good $j \in G$ to every buyer $i \in B$ with $\infty$ capacity. Clearly, the max-flow gives the required $z_{ij}$’s.

Therefore, in order to understand the optimality conditions, we may as well work with the Karush-Kuhn-Tucker (KKT) conditions for the auxiliary convex program. Let $x_{ij}, q, \mu_i, \lambda_j$ be the Lagrangian (dual) variables corresponding to the equations (1-4). An optimal solution must satisfy the KKT conditions in Table 2.

<table>
<thead>
<tr>
<th>Table 2. KKT Conditions</th>
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</thead>
<tbody>
<tr>
<td>$\forall i \in B, \forall j \in G : \mu_i = 0$</td>
</tr>
<tr>
<td>$\forall j \in G : \lambda_j = 0$</td>
</tr>
</tbody>
</table>

Claim. At any optimum, $\mu_i = 0$, $\forall i \in B$ and $\lambda_j = 0$, $\forall j \in G$.

Proof. $\mu_i \neq 0 \Rightarrow y_i = 0 \Rightarrow$ the optimal solution has cost $-\infty$. However, we may easily construct a feasible point in the polytope, where the cost is some real value, therefore all $\mu_i$’s are zero. Similarly, $\lambda_j \neq 0 \Rightarrow p_j = 0 \Rightarrow y_i = 0$, for some $i \in B$. Hence, all $\lambda_j$’s are zero. \qed
Table 2. KKT conditions

\[ \forall i \in B \quad : \quad \frac{m_i}{y_i} = \sum_{j \in G} u_{ij} x_{ij} - \mu_i \quad (8) \]

\[ \forall i \in B, \forall j \in G \quad : \quad (u_{ij} y_i - p_j) x_{ij} = 0 \quad (9) \]

\[ \forall j \in G \quad : \quad -\sum_{i \in B} x_{ij} - \lambda_j + q = 0 \quad (10) \]

\[ \left( \sum_{j \in G} p_j - \sum_{i \in B} m_i \right) q = 0 \quad (11) \]

\[ \forall i \in B, \forall j \in G \quad : \quad x_{ij}, \lambda_j, \mu_i, q \geq 0 \quad (12) \]

\[ \forall j \in G \quad : \quad -p_j \lambda_j = 0 \quad (13) \]

\[ \forall i \in B \quad : \quad -y_i \mu_i = 0 \quad (14) \]

Putting \( \mu_i = 0 \) and \( \lambda_j = 0 \) in the KKT conditions (8-12), we get,

\[ \forall i \in B \quad : \quad m_i = \sum_{j \in G} u_{ij} x_{ij} y_i \quad (15) \]

\[ \forall i \in B, \forall j \in G \quad : \quad (u_{ij} y_i - p_j) x_{ij} = 0 \quad (16) \]

\[ \forall j \in G \quad : \quad \sum_{i \in B} x_{ij} = q \quad (17) \]

\[ : \quad \left( \sum_{j \in G} p_j - \sum_{i \in B} m_i \right) q = 0 \quad (18) \]

\[ \forall i \in B, \forall j \in G \quad : \quad x_{ij}, q \geq 0 \]

From (15-18), \[ \sum_{i \in B} m_i = \sum_{i \in B} \sum_{j \in G} p_j x_{ij} = \sum_{j \in G} \sum_{i \in B} p_j x_{ij} = \sum_{j \in G} p_j q \Rightarrow q = 1 \]

Proposition 1. Let \((y, p) \in O_{aux}\) be an optimal solution to the auxiliary convex program. Then \(p\) is a market equilibrium price vector.

Proof. As \(q = 1\), interpreting \(X = [x_{ij}]\) as an allocation, we see that conditions (15-17) imply that the market clearing constraint holds at the price vector \(p\). Further, using condition 2, we have \(x_{ij} > 0 \Rightarrow y_i u_{ij} = p_j\). As \((y, p) \in O_{aux}\), we also have, \(\forall i \in B, \forall j \in G : u_{ij} y_i \leq p_j\). Putting these two together, it is easily verified that the optimal goods constraint is also satisfied. \(\square\)

Proposition 2.

(i) The auxiliary convex program admits a unique optimal solution.
(ii) Equilibrium prices are unique and allocations form a polyhedral set.

Proof. Part (i) follows from the fact that the cost function is strictly concave, and part (ii) follows from the KKT conditions. \(\square\)

Let \((y, p) \in O_{aux}\) be the unique optimum solution to the auxiliary convex program. Let \(X = \{X = [x_{ij}]_{i \in B, j \in G} \mid (y, p, X) \text{satisfies (8-14)}\}\). Note that \(X\) is a convex set. As argued in the proof of
Proposition 1, we may think of \( X \in \mathbb{X} \) as an equilibrium allocation and \( p \) as the equilibrium price. Now, we define \( Z = [z_{ij}] \) w.r.t. \( X \in \mathbb{X} \) as \( z_{ij} = x_{ij}p_{ij}, \forall i \in B, \forall j \in G \). In other words, \( z_{ij} \) is the money spent by buyer \( i \) on good \( j \) at the equilibrium allocation \( X \). We refer to \( Z \) as an equilibrium money allocation. It easily follows that \( (y, p, Z) \) is an optimum solution to the main convex program. Note that there is an \( X^a \in \mathbb{X} \) such that the bipartite graph \( G = (B, G, E) \), where \( E = \{(i, j) \in B \times G \mid x_{ij}^a > 0\} \), is acyclic. Let \( Z^a \) be the equilibrium money allocation w.r.t. \( X^a \). The following corollary follows from the the KKT condition (16).

**Corollary 3.** At the optimum solution \( (y, p, Z^a) \), \( z_{ij}^a(u_{ij}y_i - p_j) = 0, \forall (i, j) \in (B \times G) \).

The conditions in Corollary 3 are called complementarity conditions, as mentioned in the Introduction. It says that for every pair of \( (i, j) \in (B \times G) \), either \( z_{ij} = 0 \) or \( u_{ij}y_i - p_j = 0 \). In other words, when \( z_{ij} > 0 \), \( u_{ij}y_i - p_j = 0 \). The next proposition asserts that \( (y, p, Z^a) \) is in fact a vertex of \( O \).

**Proposition 4.** The point \( (y, p, Z^a) \) is a vertex of \( O \).

*Proof.* Consider the bipartite graph \( G = (B, G, E) \), where \( E = \{(i, j) \in B \times G \mid z_{ij}^a > 0\} \). Note that \( G \) is acyclic, hence it is a forest. Let \( k \) be the number of edges in \( E \), and each edge gives a tight constraint of (1), i.e., \( u_{ij}y_i - p_j = 0 \). Since \( (y, p, Z^a) \) is an optimum point, all \( y_i \)'s and \( p_j \)'s are non-zero.

There are \( mn + m + n \) variables in the convex program, so at a vertex in \( O \), at least \( mn + m + n \) linearly independent (l.i.) constraints must be tight. Hence, we need to show \( mn + m + n \) l.i. tight constraints in \( O \) at \( (y, p, Z^a) \). We show that \( k \) constraints of (1), \( m \) constraints of (5), \( n \) constraints of (6), and \( mn - k \) constraints of (7) are tight, resulting in total \( mn + m + n \) constraints and we show that they all are l.i., hence proving the proposition.

Since \( mn - k \) \( z_{ij} \)'s are zero at \( (y, p, Z^a) \), we have \( mn - k \) l.i. tight constraints of (7). Next, we eliminate all the \( z_{ij} \)'s, which are zero, from the constraints (5) and (6). It is easy to see that we have \( k \) constraints of (1), \( m \) constraints of (5), and \( n \) constraints of (6), which are tight. The only thing remaining is that they are all l.i.. The table below describes all the \( m + n + k \) tight constraints. There are \( m + n + k \) columns and last \( k \) columns correspond to the \( k \) non-zero \( z_{ij} \)'s. We show the all the columns are l.i., i.e., there is no linear relation among them.

<table>
<thead>
<tr>
<th>( y_1 )</th>
<th>( y_2 )</th>
<th>( \cdots )</th>
<th>( y_m )</th>
<th>( p_1 )</th>
<th>( p_2 )</th>
<th>( \cdots )</th>
<th>( p_n )</th>
<th>( z_{11j1} )</th>
<th>( z_{i2j2} )</th>
<th>( \cdots )</th>
<th>( z_{ikjk} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( u_{11} )</td>
<td>( \cdots )</td>
<td>( u_{1n} )</td>
<td>( -1 )</td>
<td>( \cdots )</td>
<td>( -1 )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( R_1 )</td>
<td>( u_{12} )</td>
<td>( \cdots )</td>
<td>( -1 )</td>
<td>( \cdots )</td>
<td>( -1 )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( u_{21} )</td>
<td>( \cdots )</td>
<td>( \vdots )</td>
<td>( \vdots )</td>
<td>( \vdots )</td>
<td>( \vdots )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( R_2 )</td>
<td>( -1 )</td>
<td>( \cdots )</td>
<td>( 1 )</td>
<td>( \cdots )</td>
<td>( \cdots )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( R_3 )</td>
<td>( -1 )</td>
<td>( \cdots )</td>
<td>( 1 )</td>
<td>( \cdots )</td>
<td>( \cdots )</td>
<td></td>
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</tr>
</tbody>
</table>

If there is a linear relation \( (lr) \) among these columns, then clearly it has to contain some columns of \( y_i \)'s, some columns of \( p_j \)'s and some columns of \( z_{ij} \)'s. Let the column \( y_k \) be there in \( lr \) and \( \alpha_k \) be its coefficient. Now, consider the connected component \( C \) of \( G \), which contains buyer \( k \). To kill the coordinate of \( y_k \) in \( lr \), the columns corresponding to all the buyers \( (y_i \)'s), and goods \( (p_j \)'s) in \( C \) have to
be present and the coefficients are positive multiple of $\alpha_k$. These positive multiples are some fraction of product of utilities. This results in a vector $v$, which has zero coordinates in $R_1$ as shown in above table.

Next, to kill the coordinates of $R_2$ in $v$, we get $l$ linear equations in the coefficients $\alpha_e$ of $z_e$’s $(e \in C)$, where $l$ is the number of goods in $C$. Each $\alpha_e$ appears exactly once in one of the linear equation. The sum of all these linear equations is $\sum_{e \in C} \alpha_e = c \cdot \alpha_k$, where $c$ is some positive constant. By choosing any $\alpha_e$’s such that all the $l$ linear equations satisfy will kill the coordinates of $R_2$ in $v$.

Now, to kill the coordinates of $R_3$ in $v$, we get $r$ linear equations in the coefficients $\alpha_e$ of $z_e$’s $(e \in C)$, where $r$ is the number of buyers in $C$. Each $\alpha_e$ appears exactly once in one of the linear equation. The sum of all these $r$ linear equations is $\sum_{e \in C} \alpha_e = 0$. This implies $\alpha_k = 0$, and hence the contradiction. $\square$

Remark 5. The auxiliary program itself captures the equilibrium prices at the optimal solution, though not necessarily at one of its vertices. Since there are $m + n$ variables in $O_{aux}$, every vertex requires $m + n - 1$ tight inequalities of $[1]$ (one is coming from $[2]$). Therefore, only those instances for which the bipartite graph $G$ (at optimum), as defined above, is a tree can be at a vertex of $O_{aux}$.

3 A Simplex-like Algorithm

We begin with some notation. Henceforth, we denote the input to the Fisher market problem by $(U, m)$. The set of buyers and the set of goods are implicit. We use $g_j$ and $b_i$ to denote the good $j$ and buyer $i$ respectively. For convenience, we assume that $u_{ij} > 0, \forall i \in B, \forall j \in G$.

Now, we turn our attention to the polytope $O$ defined in the previous section. We have shown that there exists a vertex $v = (y, p, Z)$ of the polytope $O$ which captures the equilibrium prices and an equilibrium money allocation. An important property of $v$ is that it satisfies the complementarity conditions $\forall i \in B, \forall j \in G, z_{ij}(u_{ij}y_i - p_j) = 0$. In other words, every buyer spends money only on her optimal goods.

Definition 6. A vertex $v = (y, p, Z)$ of $O$ is called special if $z_{ij}(u_{ij}y_i - p_j) = 0, \forall i \in B, \forall j \in G$.

It is easy to see that if $v = (y, p, Z)$ is a special vertex, then it corresponds to a solution for an instance of the Fisher market problem. Namely, let $B' = \{i \in B \mid y_i \neq 0\}, G' = G$ and $U'$ be $U$ restricted to $B' \times G'$. Further, for $i \in B'$, let $m'_i = \sum_{j \in G} z_{ij}$. Clearly, $v$ corresponds to a solution of $(U', m')$. Our goal is to find a special vertex for which $m' = m$.

3.1 Characterization of Special Vertices

Let $v = (y, p, Z)$ be a special vertex of $O$. W.l.o.g., we may assume that all $y_i$’s and all $p_j$’s are non-zero at $v$, because if $p_j = 0$ for some $j \in G$ at $v$, then $v$ is a trivial point, i.e., all coordinates are zero, and if $y_k = 0$ for some $k \in B$ at $v$, then there is an adjacent vertex $v' = (y', p', Z')$ to $v$, where $p' = p, Z' = Z, y_i = y_i, \forall i \neq k$, and $y_k' = \min_{j \in G} \frac{\bar{p}_j}{u_{ij}}$.

Now we describe a combinatorial characterization of $v$. Towards this, we define $E(v)$ and $F(v)$ as follows:

$$E(v) = \{(i, j) \in B \times G \mid u_{ij}y_i = p_j\} \quad \text{and} \quad F(v) = \{(i, j) \in B \times G \mid z_{ij} > 0\}$$

The elements in $E(v)$ and $F(v)$ are called tight and non-zero edges respectively. By definition, $F(v) \subseteq E(v)$. Let $G(E(v), F(v))$ be the graph, whose vertices are the connected components $C_1, C_2, \ldots$ of the bipartite graph $(B, G, F(v))$, and there is an edge between $C_i$ and $C_j$ in $G(E(v), F(v))$, if there is at least one edge in $E(v) - F(v)$ between the corresponding components of $(B, G, F(v))$.

We say that buyer $i$ belongs to a vertex $C$ of $G(E(v), F(v))$, if buyer $i$ lies in the corresponding component of $(B, G, F(v))$. We call a connected component of $G$ as simply a component of $G$. 
Definition 7. W.r.t. \( v = (y, p, Z) \),

- **surplus** of buyer \( i \) is defined to be the non-negative value \( m_i - \sum_{j \in G} z_{ij} \).
- A buyer is called a **zero surplus** buyer if its surplus is zero, otherwise it is called a **positive surplus** buyer.
- A component of \((B, G, F(v))\) is called **saturated** if all buyers in that component are zero surplus buyers, otherwise it is called **unsaturated**.
- A vertex of \( G(E(v), F(v)) \) is called **saturated** if the corresponding component of \((B, G, F(v))\) is saturated, otherwise it is called **unsaturated**.

Theorem 8. \( v \) has following properties:

- Every component of \((B, G, F(v))\) contains at most one positive surplus buyer.
- Every component of \( G(E(v), F(v)) \) has at least one saturated vertex.

Proof. If a component of \((B, G, F(v))\) contains more than one positive surplus buyers, then the \( z_{ij} \)'s in that component may be modified such that the same set of inequalities are tight before and after the modification, i.e., \( v \) is not a vertex.

Similarly, if a component of \( G(E(v), F(v)) \) does not have a saturated vertex, then the \( p_j \)'s in that component may be scaled uniformly such that the same set of inequalities are tight before and after the scaling, hence a contradiction. \( \square \)

Corollary 9. If \((U, m)\) are algebraically independent (i.e., no algebraic relation among them), then

- the bipartite graph \((B, G, E(v))\) is a forest. Hence there is at most one edge in \( E(v) - F(v) \) between any two components of \((B, G, F(v))\).
- Every component of \( G(E(v), F(v)) \) has exactly one saturated vertex.

Lemma 10. Let \( v \) be a special vertex of \( O \). Then

(i) \((B, G, F(v))\) is acyclic.
(ii) If \((U, m)\) are algebraically independent, then \((B, G, E(v))\) is acyclic and the number of positive surplus buyers is \( |E(v) - F(v)| \).

Proof. Since \( v \) is a vertex of \( O \), therefore \((B, G, F(v))\) is acyclic. Part (ii) follows from Theorem 8 and Corollary 9. \( \square \)

In general, a simplex-like pivoting algorithm moves from a vertex to an adjacent vertex such that the cost function increases. Therefore, we first describe the AdjacentVertex procedure which do the same for the main convex program.

3.2 AdjacentVertex Procedure

For convenience, we assume that \((U, m)\) are algebraically independent. The AdjacentVertex procedure, given in Table 3, can be easily extended for the general \((U, m)\) (see Appendix B). The procedure takes a special vertex \( v \) and outputs another special vertex \( v' \) adjacent to \( v \), such that the cost function increases. If \( v \) is optimum, then it outputs \( v' = v \).

Otherwise, there is a component \( C \) of \( G(E(v), F(v)) \) containing an unsaturated vertex. Clearly \( C \) is a tree and there is exactly one saturated vertex, say \( C_s \), in \( C \) (Corollary 9). We consider \( C \) as the rooted tree with root \( C_s \). We pick an edge \( e \) between \( C_s \) and an unsaturated vertex, say \( C_u \), in \( C \). Let \((b_i, g_j)\) be the edge in \( E(v) - F(v) \) corresponding to \( e \). Note that, at vertex \( v \) both \( z_{ij} \geq 0 \) and \( u_{ij}y_i - p_j \leq 0 \) are tight. There are two cases depending on where \( b_i \) belongs: \( C_s \) (Case 1) or \( C_u \) (Case
Table 3. AdjacentVertex Procedure

```
AdjacentVertex(v)
    v' ← v;
    if v is optimum then
        return v';
    C ← component of G(E(v), F(v)) containing an unsaturated vertex;
    C_s ← saturated vertex in C;
    C_u ← unsaturated vertex, adjacent to C_s, in C;
    e ← edge between C_s and C_u;
    (b_i, g_j) ← edge in E(v) − F(v) corresponding to e;
    if (b_i, g_j) is from C_s to C_u then
        v' ← adjacent vertex obtained by relaxing u_ij y_i ≤ p_j;
    else v' ← adjacent vertex obtained by relaxing z_ij ≥ 0;
    return v';
```

2). In both the cases the basic idea for the pivot is to increase prices of goods in C_u so that more money of unsaturated buyers is spent, and thereby C_u moves towards saturation. This in turn also increases the cost.

**Case 1:** We get a new vertex v', adjacent to v in O, by relaxing the inequality $u_{ij} y_i = p_j$ at v. Let $T_u$ be the subtree of C rooted at $C_u$ and $J_u$ be the set of goods in the components of $(B, G, F(v))$ corresponding to the vertices of $T_u$. v' may also be obtained by increasing the prices of the goods in $J_u$ uniformly and by modifying $y_i$'s and $z_{ij}$'s accordingly till a new inequality becomes tight. Table 4 lists the three possible cases for the new inequality.

Table 4. Different cases for the new tight inequality

<table>
<thead>
<tr>
<th>Case</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>A non-zero edge $(b_k, g_l)$ becomes zero, i.e., $z_{kl} \geq 0$ becomes tight.</td>
</tr>
<tr>
<td>2.</td>
<td>A non-tight edge $(b_k, g_l)$ becomes tight, i.e., $u_{kl} y_k \leq p_l$ becomes tight.</td>
</tr>
<tr>
<td>3.</td>
<td>An unsaturated vertex in C becomes saturated, i.e., $\sum_{l \in G} z_{kl} \leq m_k$ becomes tight, where buyer $k$ is a positive surplus buyer w.r.t. v.</td>
</tr>
</tbody>
</table>

**Case 2:** We get a new vertex v', adjacent to v in O, by relaxing the inequality $z_{ij} = 0$ at v. Let $J$ be the set of goods in the components of $(B, G, F(v))$ corresponding to the vertices of C. v' may also be obtained by increasing the prices of the goods in $J$ uniformly and by modifying the $y_i$'s and $z_{ij}$'s accordingly till a new inequality becomes tight (Table 4).

Both the cases result in the new vertex v' adjacent to v in O, where $p$ as well as $y$ increase monotonically and $\sum_{j \in G} p_j$ as well as $\sum_{i \in B} y_i$ increase strictly going from v to v'. Hence the cost function value increases strictly going from v to v'. Note that v' is also a special vertex of O. From the above discussion, the following lemma is straightforward.

**Lemma 11.** If a special vertex v is not optimum, then there exists an adjacent special vertex v' such that the value of cost function is more at v' than v.
3.3 The Algorithm

There may be many simplex-like paths in $O$ to reach at the optimum vertex using different pivoting rules. Algorithm 1 traces a particular simplex-like path in $O$, where the pivoting rule is such that there is at most one buyer with a positive surplus at every vertex on the path. In this algorithm, we do not consider the components, which contain only a single buyer.

**Algorithm 1.** A Simplex-like Pivoting Algorithm

\[
U' \leftarrow \langle u_{11}, \ldots, u_{1n} \rangle; \quad m' \leftarrow \langle m_1 \rangle;

v \leftarrow \text{special vertex corresponds to the solution of } (U', m');

i \leftarrow 2;

\text{while } i \leq m \text{ do}

\text{ /* Note that the inequality } y_i \geq 0 \text{ is tight at } v */

\text{while surplus of buyer } i \text{ w.r.t. } v \text{ is non-zero do}

\text{v} \leftarrow \text{AdjacentVertex}(v);

i \leftarrow i + 1;
\]

There are two types of iterations of the inner while loop, one in which we relax the inequality $z_{kl} \geq 0$ (Type 1) and the other in which we relax the inequality $u_{kl}y_k \leq p_l$ (Type 2) for some $(b_k, g_l)$. Consider the inner while loop for buyer $i$ and let $v$ be the current special vertex. The component $C$ of $G(E(v), F(v))$ containing buyer $i$ has exactly two vertices, one saturated ($C_s$) and one unsaturated ($C_u$), and an edge $(b_k, g_l)$ between them. Note that buyer $i$ belongs to $C_u$, and $z_{kl} = 0$ and $u_{kl}y_k - p_l = 0$ at $v$. Now, consider the tree $T$ in $(B, G, E(v))$ rooted at buyer $i$. The edges are directed downwards, i.e., away from the root. We increase the prices of the goods uniformly in $T$ in order to decrease the surplus of buyer $i$. This increases the flow on the edges, which are from a buyer to a good (forward) and decreases the flow on the edges, which are from a good to a buyer (backward).

Therefore, when $(b_k, g_l)$ be such that $g_l \in C_u$ and $b_k \in C_s$, we need to relax $u_{kl}y_k \leq p_l$, and when $g_l \in C_s$ and $b_k \in C_u$, we need to relax $z_{kl} \geq 0$ in order to increase the prices. It is also clear that during the price increase, only backward edges may be deleted. Moreover, since the prices of the goods in $T$ increase, buyers in $T$ may become interested in the goods outside $T$, and it implies that only forward edges may be added. **Note that in each of the two cases the pivoting turns out to be the complementary pivot**, i.e., relax $z_{kl} = 0$ if $u_{kl}y_k - p_l = 0$ just became tight at $v$, else relax $z_{kl} = 0$, resembling Lemke-Howson scheme.

**Remark 12.** Algorithm 1 provides a polyhedral interpretation to a sequential run of the so called Basic Algorithm in [7], where buyers are added one at a time.

4 Running Time Analysis

In this section, we describe the time analysis of Algorithm 1 and show that it is strongly polynomial for many special cases.

**Lemma 13.** Algorithm 1 takes at most $(m + n \cdot 2^{m+n})$ iterations.
Proof. Consider the iterations of Type 2 of the inner while loop, where we relax the tight inequality \( u_{kl}y_k \leq p_l \) for some \((b_k, g_l)\). Let \( C^j_s \) be the component containing buyer \( k \) in the \( j \)-th such iteration. Note that \( C^j_s \) is a saturated component. Let \( B^j \) be the set of buyers and \( G^j \) be the set of goods in \( C^j_s \), and \( S^j = B^j \cup G^j \). Since prices monotonically increase, therefore all \( S^j \)'s are distinct. The total number of distinct \( S^j \)'s are clearly bounded by \( 2^m+n \), and in every \( n \) iterations of inner while loop, one iteration has to be of Type 2, therefore the number of iterations of the algorithm is bounded by \((m+n*2^{m+n})\).

Remark 14. A more refined bound is \( 2^{m+n+1} \).

**Theorem 15.** Algorithm 1 is strongly polynomial when either the number of buyers or goods is constant.

Proof. Without loss of generality, we assume that \((U, m)\) are algebraically independent. For the general \((U, m)\), a similar proof may be worked out.

It is enough to show that the inner while loop takes a strongly polynomial number of iterations for every buyer \( i \). Let \( C^j \) be the component of \( G(E(v), F(v)) \), which contains buyer \( i \) in the \( j \)-th iteration of the inner while loop for buyer \( i \). If surplus of buyer \( i \) is not zero, then \( C^j \) contains exactly one saturated vertex, say \( C^j_s \), and one unsaturated vertex, say \( C^j_u \). Note that buyer \( i \) belongs to \( C^j_u \).

Let \((b_k, g_l)\) be the edge between \( C^j_u \) and \( C^j_s \), and \( P_j \) be the path starting from buyer \( i \) and ending with the edge \((b_k, g_l)\) in \((B, G, E(v))\).

Claim. All \( P_j \)'s are distinct.

Proof. Recall that when the edge \((b_k, g_l)\) is such that buyer \( k \) belongs to \( C^j_s \), we relax the inequality \( u_{kl}y_k \leq p_l \), and when buyer \( k \) belongs to \( C^j_u \), we relax the inequality \( z_{kl} \geq 0 \). In other words, we add the edge \((b_k, g_l)\) when buyer \( k \) belongs to \( C^j_u \) and delete it when buyer \( k \) belongs to \( C^j_s \).

We show that all \( P_j \)'s, which end in a good, are distinct, and a similar argument may be worked out for the case when they end in a buyer. A path \( P_j \) may repeat only when the last edge, say \( e \), is deleted and added again, and this is possible only if some other edge more near to buyer \( i \) than \( e \) in \( P_j \) is deleted. The induction on the length of \( P_j \) proves the claim, because the edges between buyer \( i \) and the goods never break (buyer \( i \) always lies in \( C^j_u \)).

Since the length of any \( P_j \) is at most \( 2 \cdot \min(m, n) \), therefore it is a constant when either \( m \) or \( n \) is constant. Hence the total number of distinct \( P_j \)'s are bounded by a polynomial in \( m \) (if \( n \) is constant) or \( n \) (if \( m \) is constant). Hence the length of the simplex-like path in the Algorithm 1 is strongly polynomial when either the number of buyers or goods is constant.

**Theorem 16.** Algorithm 1 is strongly polynomial when \( \forall i \in B, \forall j \in G, u_{ij} = \alpha^{k_{ij}}, \text{ where } 0 \leq k_{ij} \leq \text{poly}(m, n) \) and \( \alpha > 0 \).

Proof. We only need to show that for every buyer \( i \), the inner while loop takes a strongly polynomial number of iterations. Consider the iterations of inner while loop for a buyer \( a \). We monitor the values of \( \frac{u_{ia}}{p_a} \) \( \forall b \in G \). Note that \( \frac{u_{ia}}{p_a} \) for a good \( b \) remains same until both buyer \( a \) and good \( b \) are in the same component of \( G(E(v), F(v)) \), otherwise it strictly increases. Let \( C^j \) be the component of \( G(E(v), F(v)) \), which contains buyer \( a \) in the \( j \)-th iteration. If surplus of buyer \( a \) is not zero, then \( C^j \) contains exactly one saturated vertex, say \( C^j_s \), and one unsaturated vertex, say \( C^j_u \). Note that buyer \( a \) belongs to \( C^j_u \).

Let \((b_k, g_l)\) be the edge between \( C^j_u \) and \( C^j_s \). There are two types of iterations, one in which we relax the inequality \( z_{kl} \geq 0 \) (Type 1) and the other in which we relax the inequality \( u_{kl}y_k \leq p_l \) (Type 2). Let \( z_{kl} \geq 0 \) is relaxed in the \( j \)-th iteration, and \( b_u, g_j, b_l, \ldots, g_j, b_k, g_l \) be the path from \( b_u \) to \( g_l \) in
Clearly, \( \frac{y_i}{p_i} = \frac{u_{ij_1} \ldots u_{ij_k}}{u_{ij_2} \ldots u_{ij_{k+1}} u_{il}} \) (using the tight inequalities \( u_{ij} y_i \leq p_j \)), and the value of \( \frac{y_i}{p_i} \) strictly increases when iteration of Type 1 occurs. Now, we consider the values of \( \log_\alpha \frac{y_i}{p_i}, \forall j \in G \). Clearly, these values monotonically increase when an iteration of Type 1 occurs. Since for every \( j \in G \), the value of \( \log_\alpha \frac{y_i}{p_i} \) might be at most \( n \ast \text{poly}(m,n) \), therefore for every buyer \( i \), the number of iterations of inner while loop is bounded by \( n^2 \ast \text{poly}(m,n) \).

Theorem 16 may be easily generalized to handle the case when some \( u_{ij} \)’s are zero. Many easy cases like all utilities are 0/1, non-zero utilities form a tree etc. may also be easily shown to be strongly polynomial in Algorithm 1.

### 5 Experimental Results

In this section, we report the experimental results of Algorithm 1. We ran Algorithm 1 on random instances of the Fisher market (i.e., \((U, m)\) are generated uniformly at random), while keeping the number of buyers and goods same (i.e., \(m = n\)). For each value of \( m \in \{4, 8, 12, 16, 20, 24\} \), we ran 100 experiments. Table 5 summarizes the results in terms of the minimum (best), maximum (worst) and mean (average) number of pivoting steps taken by Algorithm 1.

<table>
<thead>
<tr>
<th># buyers/goods</th>
<th>4</th>
<th>8</th>
<th>12</th>
<th>16</th>
<th>20</th>
<th>24</th>
</tr>
</thead>
<tbody>
<tr>
<td>min</td>
<td>6</td>
<td>31</td>
<td>84</td>
<td>136</td>
<td>245</td>
<td>223</td>
</tr>
<tr>
<td>max</td>
<td>24</td>
<td>80</td>
<td>168</td>
<td>235</td>
<td>320</td>
<td>514</td>
</tr>
<tr>
<td>mean</td>
<td>12.5</td>
<td>50.9</td>
<td>113.1</td>
<td>186.9</td>
<td>279.8</td>
<td>408.9</td>
</tr>
</tbody>
</table>

Clearly, the number of steps seem to increase quadratically with the size of instances, and even the worst case instance for each value of \( m \) requires fewer than \( 2m^2 \) steps. Therefore, Algorithm 1 should have a much better bound.

### 6 Conclusion

We have presented a novel convex optimization formulation for the Fisher market problem whose feasible set is a polytope and it is guaranteed that there is a vertex of this polytope which is an optimal solution. Exploiting this, we have developed a simplex-like vertex-marching algorithm which runs in strongly polynomial time for many special cases.

We have also elaborated on the connection of our algorithm with an LCP formulation and the Lemke/Lemke-Howson scheme. We have argued that perhaps this formulation is more rewarding, both practically and conceptually. The variables \( y_i \)’s are the key to the formulation and have led to a generalization to Arrow-Debreu markets as well.

We feel that the strongly polynomial algorithm by Orlin is neither polytopal nor very intuitive. The algorithms, which are polytopal and simplex-like are generally easier to understand, simpler to implement using standard math libraries, and run faster in practice. Therefore, an obvious open problem is to give a strongly polynomial, simplex-like algorithm; even a polynomial bound will be interesting. Another open problem is to give a linear programming formulation that captures the equilibrium prices for the Fisher market. Therefore, it will be interesting to construct a linear cost function on our polytope so that optimum vertex gives the equilibrium prices.
References

A Fisher Markets with Transportation Costs

We generalize the Fisher market model to incorporate transportation costs as well, where in addition to all the inputs, a transportation cost matrix $C = [c_{ij}]$, where $c_{ij}$ is the cost of transporting unit amount of good $j$ to buyer $i$, is also given. Independently, Chakraborty et al. [16] also give a similar formulation for this generalization along with an algorithm to compute $\epsilon$-approximate equilibrium.

Note that, by scaling $u_{ij}$’s and $c_{ij}$’s appropriately, we may assume that $q_j$’s are unit. The problem is again to find the equilibrium prices $(p = (p_j)_{j \in G})$ and allocation $(X = [x_{ij}]_{i \in B, j \in G})$ such that the market clears and every buyer receives a maximum utility bundle subject to her budget constraint. Note that $c_{ij}$’s also have to be taken into account in this model in the calculation of optimal goods.

Formally, the equilibrium prices and allocation must satisfy the following two conditions:

- **Market Clearing:** There is neither deficiency nor surplus of any good and the money of all the buyers is exhausted, i.e., $\forall j \in G$, $\sum_{i \in B} x_{ij} = 1$ and $\forall i \in B$, $\sum_{j \in G} x_{ij} (p_j + c_{ij}) = m_i$.
- **Optimal Goods:** Every buyer buys only those goods which give her the maximum utility per unit of money, i.e., if $x_{ij} > 0$ then $\frac{u_{ij}}{p_j + c_{ij}} = \max_{k \in G} \frac{u_{ik}}{p_k + c_{ik}}$.

The optimal solution of the Eisenberg-Gale convex program [6] captures equilibrium solution for the Fisher market, in turn also ensures existence and uniqueness of the equilibrium prices. However, it does not seem possible to extend the Eisenberg-Gale convex program to capture equilibrium solution for the Fisher market with transportation costs.

Interestingly, the optimal solution of the convex formulation, given in Table 6, captures the equilibrium prices (if they exist) for this model, and it is a simple extension of the convex program in Table 1. It also gives the conditions for the existence of equilibrium solution and proves the uniqueness of the equilibrium prices.

**Table 6. Convex Program**

| maximize | $\sum_{i \in B} m_i \log y_i - e$ |
| subject to | $\forall i \in B, \forall j \in G$ | $u_{ij} y_i \leq p_j + c_{ij}$ |
| & $\sum_{j \in G} p_j \leq e$ |
| & $\forall i \in B$ | $y_i \geq 0$ |
| & $\forall j \in G$ | $p_j \geq 0$ |
| & | $e \geq 0$ |

Let $x_{ij}, q, \mu_i, \lambda_j, \gamma$ be the Lagrangian (dual) variables corresponding to the equations (19-23). As before, $p_j$ is interpreted as the price of good $j$, and $[x_{ij}]$ may be interpreted as the allocation. An optimal solution must satisfy the KKT conditions given in Table 7.

At optimum, clearly $y_i > 0$, $\forall i \in B \Rightarrow \mu_i = 0$, $\forall i \in B$. Putting $\mu_i = 0$ in (24) and from (24-25), we get

$$\forall i \in B : \sum_{j \in G} x_{ij} (p_j + c_{ij}) = m_i$$

$$\forall i \in B, \forall j \in G : x_{ij} > 0 \Rightarrow \frac{u_{ij}}{p_j + c_{ij}} = \frac{\sum_{j \in G} u_{ij} x_{ij}}{m_i}$$
Table 7. KKT conditions

\[
\forall i \in \mathcal{B} \quad \frac{m_i}{y_i} = \sum_{j \in \mathcal{G}} u_{ij} x_{ij} - \mu_i \tag{24}
\]

\[
\forall i \in \mathcal{B}, \forall j \in \mathcal{G} \quad (u_{ij} y_i - p_j - c_{ij}) x_{ij} = 0 \tag{25}
\]

\[
\forall j \in \mathcal{G} \quad -p_j \lambda_j = 0 \tag{26}
\]

\[
\forall j \in \mathcal{G} \quad -e \gamma = 0 \tag{27}
\]

\[
\forall i \in \mathcal{B}, \forall j \in \mathcal{G} \quad -1 = -q - \gamma \tag{28}
\]

\[
\forall j \in \mathcal{G} \quad -\sum_{i \in \mathcal{B}} x_{ij} - \lambda_j + q = 0 \tag{29}
\]

\[
\forall i \in \mathcal{B} \quad -y_i \mu_i = 0 \tag{31}
\]

\[
\forall i \in \mathcal{B}, \forall j \in \mathcal{G} \quad x_{ij}, \lambda_j, \mu_i, q, \gamma \geq 0 \tag{32}
\]

The above two conditions say that at optimum, all buyers exhaust their money and they buy only the optimal goods.

From (20) and (26-29), we get

\[
\forall j \in \mathcal{G} : \quad p_j > 0 \Rightarrow \lambda_j = 0, e > 0 \Rightarrow \gamma = 0 \Rightarrow q = 1 \Rightarrow \sum_{i \in \mathcal{B}} x_{ij} = 1
\]

The above condition says that if the price of a good is non-zero at optimum, then that good is completely sold.

Now, it is easy to check that any equilibrium solution of the Fisher market with transportation costs will satisfy all the conditions (19-32) by taking appropriate values of the remaining variables, hence it must be the optimum solution of the convex program. Since the objective cost function is strictly concave, therefore equilibrium prices are unique (if they exist).
AdjacentVertex Procedure for General $(U, m)$

```plaintext

AdjacentVertex($v$)
  $v' \leftarrow v$;
  if $v$ is optimum then
    return $v'$;
  else
    $C \leftarrow$ component of $G(E(v), F(v))$ containing an unsaturated vertex;
    $L \leftarrow$ set of tight inequalities at $v$;
    $B' \leftarrow$ set of buyers in the component of $(B, G, E(v))$ corresponding to $C$;
    $G' \leftarrow$ set of goods in the component of $(B, G, E(v))$ corresponding to $C$;
    $F'(v) = \{(b_i, g_j) \in F(v) \mid i \in B', j \in G'\}$;
    $E \leftarrow \{(b_i, g_j) \in E(v) \mid b_i$ and $g_j$ are in different components of $(B', G', F'(v))\}$;
    while $\text{rank}(L) = mn + m + n$ and $E \neq \emptyset$ do
      $G \leftarrow (B', G', F'(v))$;
      $(b_i, g_j) \leftarrow$ an edge in $E$ between $C_s$ and $C_u$ of $G$;
      if $(b_i, g_j)$ is from $C_s$ to $C_u$ then
        Relax the inequality $u_{ij}y_i \leq p_j$, which is tight at $v$;
        $L \leftarrow L - \{u_{ij}y_i \leq p_j\}$;
      else
        Relax the inequality $z_{ij} \geq 0$, which is tight at $v$;
        $L \leftarrow L - \{z_{ij} \geq 0\}$;
      /* $C_s$ and $C_u$ are merged into a new unsaturated component. */
      $F'(v) \leftarrow F'(v) + (b_i, g_j)$;
      $E \leftarrow E - (b_i, g_j)$;
    /* Now we are on an edge of $O$ */
    $v' \leftarrow$ vertex adjacent to $v$ on this edge in $O$;
  return $v'$;

Table 8. AdjacentVertex Procedure
```
