

Traditional Derivation of Demand Properties

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Implicit assumptions

In the traditional analysis of demand functions, there are a number of implicit assumptions that if not made render the analysis vacuous. Among these are:

U.1 The utility function $u: \mathbf{R}_+^n \rightarrow \mathbf{R}$ is continuous, and twice continuously differentiable on \mathbf{R}_{++}^n .

U.2 At each point $x \gg 0$, we have $u'(x) \gg 0$, which is a strong monotonicity condition.

U.3 The utility satisfies the following strong quasiconcavity condition. At each $x \gg 0$, the Hessian is negative definite on tangent planes to indifference curves. That is, for all $v \in \mathbf{R}^n$,

$$\sum_{i=1}^n \sum_{j=1}^n u_{ij}(x) v_i v_j < 0 \quad v \neq 0 \text{ and } u'(x) \cdot v = 0.$$

(Here and throughout these notes we adopt the notational convention that subscripts can be used to denote partial differentiation, so that u_i denotes $D_i u = \frac{\partial u}{\partial x_i}$, and u_{ij} denotes $D_{ij} u = \frac{\partial^2 u}{\partial x_i \partial x_j}$.)

This is equivalent to

$$(-1)^p \begin{vmatrix} u_{11} & \dots & u_{1p} & u_1 \\ \vdots & & \vdots & \vdots \\ u_{p1} & \dots & u_{pp} & u_p \\ u_1 & \dots & u_p & 0 \end{vmatrix} > 0 \quad p = 2, \dots, n.$$

In particular,

$$\begin{vmatrix} u_{11} & \dots & u_{1n} & u_1 \\ \vdots & & \vdots & \vdots \\ u_{n1} & \dots & u_{nn} & u_n \\ u_1 & \dots & u_n & 0 \end{vmatrix} \neq 0.$$

U.4 If $x \gg 0$, its indifference curve never approaches a point on the boundary of \mathbf{R}_+^n .

Attention is restricted to strictly positive price vectors p and strictly positive income m . Under these conditions, the utility maximizing consumption is always unique, satisfies the budget with equality, and is strictly positive. Furthermore, utility maximization and expenditure minimization are equivalent. That is, if x^* maximizes $u(x)$ subject to $m - p \cdot x \geq 0$ and if \hat{x} minimizes $p \cdot x$ subject to $u(x) \geq u^*$, where $u^* = u(x^*)$, then $x^* = \hat{x}$ and $p \cdot x^* = m$. Throughout these notes, $p \in \mathbf{R}_{++}^n$ is a vector of strictly positive prices, and $m > 0$ is a strictly positive

Utility maximization

The constrained maximization problem is

$$\text{maximize } u(x) \quad \text{subject to } m - p \cdot x = 0.$$

We know there is a unique interior maximizer x^* . The gradient of the constraint is $-p \neq 0$, so the Lagrange Multiplier Theorem applies. Thus there is a Lagrange multiplier λ^* so that the first-order conditions

$$u_i(x^*) - \lambda^* p_i = 0 \quad i = 1, \dots, n$$

are satisfied. Since $p \gg 0$ and each $u_i > 0$ by assumption U.2, we have

$$\lambda^* > 0.$$

The second-order conditions are that the Hessian matrix $[u_{ij}]$ be negative semidefinite under constraint, more specifically

$$\sum_i \sum_j u_{ij}(x^*) v_i v_j \leq 0 \quad \text{for all } v \text{ such that } \sum_i (-p_i) v_i = 0.$$

Since the first-order condition implies $u_i(x^*) = \lambda^* p_i$, we see that assumption U.3 guarantees that the strong second-order conditions are satisfied.

Consider the function $g: \mathbf{R}^{n+1} \times \mathbf{R}^{n+1} \rightarrow \mathbf{R}^{n+1}$ defined by the first-order conditions,

$$g^i(x, \lambda; p, m) = u_i(x) - \lambda p_i$$

for $i = 1, \dots, n$, and the constraint,

$$g^{n+1}(x, \lambda; p, m) = m - p \cdot x.$$

The Jacobian of this function with respect to (x, λ) is

$$\begin{vmatrix} u_{11} & \dots & u_{1n} & -p_1 \\ \vdots & & \vdots & \vdots \\ u_{n1} & \dots & u_{nn} & -p_n \\ -p_1 & \dots & -p_n & 0 \end{vmatrix} = \begin{vmatrix} u_{11} & \dots & u_{1n} & -\frac{1}{\lambda} u_1 \\ \vdots & & \vdots & \vdots \\ u_{n1} & \dots & u_{nn} & -\frac{1}{\lambda} u_n \\ -\frac{1}{\lambda} u_1 & \dots & -\frac{1}{\lambda} u_n & 0 \end{vmatrix} = \frac{1}{\lambda^2} \begin{vmatrix} u_{11} & \dots & u_{1n} & u_1 \\ \vdots & & \vdots & \vdots \\ u_{n1} & \dots & u_{nn} & u_n \\ u_1 & \dots & u_n & 0 \end{vmatrix}$$

where the first equality follows from the first-order conditions, and the second by multiplying the last row and last column by $-\lambda$. It follows from $\lambda^* > 0$ and U.3 this determinant is nonzero at (x^*, λ^*) , so by the Implicit Function Theorem, since u is C^2 , then x^* and λ^* are C^1 functions of (p, m) , at least locally. Thus the first-order conditions imply that

$$\begin{aligned} u_i(x^*(p, m)) - \lambda^*(p, m)p_i &= 0 & i = 1, \dots, n. \\ \text{and} \\ m - \sum_i p_i x_i^*(p, m) &= 0 \\ \text{for all } (p, m). \end{aligned} \tag{FOC}$$

The left-hand side of each of these first-order conditions can be viewed as a constant function of (p, m) , namely the zero function. So for each commodity i and each price p_j , differentiate the left-hand side of the first order condition for x_i with respect to p_j to get

$$\sum_k u_{ik} \frac{\partial x_k^*}{\partial p_j} - \frac{\partial \lambda^*}{\partial p_j} p_i - \lambda^* \delta_{ij} = 0 \quad \begin{array}{l} i = 1, \dots, n, \\ j = 1, \dots, n. \end{array} \tag{1''}$$

and the constraint to get

$$- \sum_k p_k \frac{\partial x_k^*}{\partial p_j} - x_j^* = 0 \quad j = 1, \dots, n. \tag{2''}$$

Differentiate each left-hand side with respect to m to get

$$\sum_k u_{ik} \frac{\partial x_k^*}{\partial m} - \frac{\partial \lambda^*}{\partial m} p_i = 0 \quad i = 1, \dots, n. \tag{3''}$$

and

$$1 - \sum_k p_k \frac{\partial x_k^*}{\partial m} = 0. \tag{4''}$$

For aesthetic reasons that will become clear in a moment, I want to use the first-order conditions $u_i = \lambda^* p_i$ and do a little regrouping:

$$\sum_k u_{ik} \frac{\partial x_k^*}{\partial p_j} + u_i \frac{-1}{\lambda^*} \frac{\partial \lambda^*}{\partial p_j} = \lambda^* \delta_{ij} \quad \begin{array}{l} i = 1, \dots, n, \\ j = 1, \dots, n. \end{array} \tag{1'}$$

$$\sum_k u_k \frac{\partial x_k^*}{\partial p_j} = -\lambda^* x_j^* \quad j = 1, \dots, n. \tag{2'}$$

$$\sum_k u_{ik} \frac{\partial x_k^*}{\partial m} + u_i \frac{-1}{\lambda^*} \frac{\partial \lambda^*}{\partial m} = 0 \quad i = 1, \dots, n. \tag{3'}$$

$$\sum_k u_k \frac{\partial x_k^*}{\partial m} = \lambda^*. \tag{4'}$$

We can view these in terms of n -vectors and rewrite them as

$$\begin{bmatrix} u_{i1}, \dots, u_{in}, u_i \end{bmatrix} \cdot \begin{bmatrix} \frac{\partial x_1^*}{\partial p_j}, \dots, \frac{\partial x_n^*}{\partial p_j}, \frac{-1}{\lambda^*} \frac{\partial \lambda^*}{\partial p_j} \end{bmatrix} = \lambda^* \delta_{ij} \quad \begin{array}{l} i = 1, \dots, n, \\ j = 1, \dots, n. \end{array} \quad (1)$$

$$\begin{bmatrix} u_1, \dots, u_n, 0 \end{bmatrix} \cdot \begin{bmatrix} \frac{\partial x_1^*}{\partial p_j}, \dots, \frac{\partial x_n^*}{\partial p_j}, \frac{-1}{\lambda^*} \frac{\partial \lambda^*}{\partial p_j} \end{bmatrix} = -\lambda^* x_j^* \quad j = 1, \dots, n. \quad (2)$$

$$\begin{bmatrix} u_{i1}, \dots, u_{in}, u_i \end{bmatrix} \cdot \begin{bmatrix} \frac{\partial x_1^*}{\partial m}, \dots, \frac{\partial x_n^*}{\partial m}, \frac{-1}{\lambda^*} \frac{\partial \lambda^*}{\partial m} \end{bmatrix} = 0 \quad i = 1, \dots, n. \quad (3)$$

$$\begin{bmatrix} u_1, \dots, u_n, 0 \end{bmatrix} \cdot \begin{bmatrix} \frac{\partial x_1^*}{\partial m}, \dots, \frac{\partial x_n^*}{\partial m}, \frac{-1}{\lambda^*} \frac{\partial \lambda^*}{\partial m} \end{bmatrix} = \lambda^* \quad i = 1, \dots, n. \quad (4)$$

Arranging all this in matrix terms gives

$$\begin{bmatrix} u_{11} & \dots & u_{1n} & u_1 \\ \vdots & & \vdots & \vdots \\ u_{n1} & \dots & u_{nn} & u_n \\ u_1 & \dots & u_n & 0 \end{bmatrix} \begin{bmatrix} \frac{\partial x_1^*}{\partial p_1} & \dots & \frac{\partial x_1^*}{\partial p_n} & \frac{\partial x_1^*}{\partial m} \\ \vdots & & \vdots & \vdots \\ \frac{\partial x_n^*}{\partial p_1} & \dots & \frac{\partial x_n^*}{\partial p_n} & \frac{\partial x_n^*}{\partial m} \\ \frac{-1}{\lambda^*} \frac{\partial \lambda^*}{\partial p_1} & \dots & \frac{-1}{\lambda^*} \frac{\partial \lambda^*}{\partial p_n} & \frac{-1}{\lambda^*} \frac{\partial \lambda^*}{\partial m} \end{bmatrix} = \begin{array}{c} \left[\begin{array}{cc|c} \lambda^* & 0 & 0 \\ & \ddots & \vdots \\ 0 & \lambda^* & 0 \\ \hline -\lambda^* x_1^* & \dots & -\lambda^* x_n^* & \lambda^* \end{array} \right] \end{array}. \quad (5)$$

The entries in the $(n+1) \times (n+1)$ right-hand side matrix correspond to the equations (1)–(4) according to this scheme:

$$\begin{array}{c} \left[\begin{array}{c|c} (1)_{n \times n} & (3)_{n \times 1} \\ \hline (2)_{1 \times n} & (4)_{1 \times 1} \end{array} \right] \end{array}$$

Solving this gives

$$\begin{bmatrix} \frac{\partial x_1^*}{\partial p_1} & \dots & \frac{\partial x_1^*}{\partial p_n} & \frac{\partial x_1^*}{\partial m} \\ \vdots & & \vdots & \vdots \\ \frac{\partial x_n^*}{\partial p_1} & \dots & \frac{\partial x_n^*}{\partial p_n} & \frac{\partial x_n^*}{\partial m} \\ \frac{-1}{\lambda^*} \frac{\partial \lambda^*}{\partial p_1} & \dots & \frac{-1}{\lambda^*} \frac{\partial \lambda^*}{\partial p_n} & \frac{-1}{\lambda^*} \frac{\partial \lambda^*}{\partial m} \end{bmatrix} = \begin{bmatrix} u_{11} & \dots & u_{1n} & u_1 \\ \vdots & & \vdots & \vdots \\ u_{n1} & \dots & u_{nn} & u_n \\ u_1 & \dots & u_n & 0 \end{bmatrix}^{-1} \begin{array}{c} \left[\begin{array}{cc|c} \lambda^* & 0 & 0 \\ & \ddots & \vdots \\ 0 & \lambda^* & 0 \\ \hline -\lambda^* x_1^* & \dots & -\lambda^* x_n^* & \lambda^* \end{array} \right] \end{array}. \quad (6)$$

Set

$$A = \begin{bmatrix} u_{11} & \dots & u_{1n} & u_1 \\ \vdots & & \vdots & \vdots \\ u_{n1} & \dots & u_{nn} & u_n \\ u_1 & \dots & u_n & 0 \end{bmatrix}^{-1},$$

which exists by assumption U.3. Then we have

$$\frac{\partial x_i^*}{\partial m} = \lambda^* a_{i,n+1}$$

and

$$\frac{\partial x_i^*}{\partial p_j} = \lambda^* a_{ij} - \lambda^* x_j^* a_{i,n+1} = \lambda^* a_{ij} - x_j^* \frac{\partial x_i^*}{\partial m}.$$

In particular,

$$\frac{\partial x_i^*}{\partial p_i} = \lambda^* a_{ii} - x_i^* \frac{\partial x_i^*}{\partial m}. \quad (7)$$

The natural question is, what is the economic interpretation of $\lambda^* a_{ij}$? The answer lies in the expenditure minimization problem.

Utility maximization and expenditure minimization

Fix (p, m) and let $v = u(x^*(p, m)) = v(p, m)$. Consider the problem

$$\underset{x}{\text{minimize}} p \cdot x \quad \text{subject to } u(x) \geq v.$$

When is this problem equivalent to the utility maximization problem?

To answer that let me introduce a new definition. We say that the utility function $u: X \rightarrow \mathbf{R}$ is **locally nonsatiated at x** if for every $\varepsilon > 0$, there is some $z \in X$ satisfying $\|x - z\| < \varepsilon$ and $u(z) > u(x)$. (Note that this is a joint assumption on X and u .)

Lemma 1 (Budget exhaustion) *Let $u: X \rightarrow \mathbf{R}$ and suppose $\bar{x} \in X$ maximizes $u(x)$ over the budget set $\beta(p, m) = \{x \in X : p \cdot x \leq m\}$. If u is locally nonsatiated at \bar{x} , then \bar{x} exhausts the budget, that is,*

$$p \cdot \bar{x} = m.$$

Proof: If $p \cdot \bar{x} < m$, then there is an $\varepsilon > 0$ such that $y \in X$ and $\|y - \bar{x}\| < \varepsilon$ implies $p \cdot y < m$, and thus $y \in \beta(p, m)$. Thus $u(\bar{x}) \geq u(y)$ for all such y , so u is not locally nonsatiated at \bar{x} . The lemma now follows by contraposition. ■

Proposition 1 *Let $u: \mathbf{R}_+^n \rightarrow \mathbf{R}$ be locally nonsatiated everywhere.*

1. If \bar{x} maximizes $u(x)$ subject to $p \cdot x \leq m$, then \bar{x} minimizes $p \cdot x$ subject to $u(x) \geq u(\bar{x})$.
2. If u is also continuous, and \bar{x} minimizes $p \cdot x$ subject to $u(x) \geq u(\bar{x})$, and $p \cdot \bar{x} > 0$, then \bar{x} maximizes $u(x)$ subject to $p \cdot x \leq p \cdot \bar{x}$.

Proof: (1) Assume \bar{x} maximizes $u(x)$ subject to $p \cdot x \leq m$. Then clearly $u(y) > u(\bar{x})$ implies $p \cdot y > p \cdot \bar{x}$. Now suppose by way of contradiction that $u(y) = u(\bar{x})$, but $p \cdot y < p \cdot \bar{x}$. Since u is locally nonsatiated at y there is some $z \in X$ close to y with $p \cdot z < p \cdot \bar{x}$ and $u(z) > u(y) = u(\bar{x})$, which contradicts the maximality of \bar{x} over the budget set.

(2) Assume \bar{x} minimizes $p \cdot x$ subject to $u(x) \geq u(\bar{x})$, and $p \cdot \bar{x} > 0$. Then clearly $p \cdot y < p \cdot \bar{x}$ implies $u(y) < u(\bar{x})$. Now consider the case $p \cdot y = p \cdot \bar{x} > 0$. Then for $0 \leq \lambda < 1$ we have $p \cdot \lambda y < p \cdot \bar{x}$, so $u(\lambda y) < u(\bar{x})$. Since u is continuous $u(y) \leq u(\bar{x})$. Thus $p \cdot y \leq p \cdot \bar{x}$ implies $u(y) \leq u(\bar{x})$. ■

The assumption that $p \cdot \bar{x} > 0$ in part (2) above is needed, if we wish to allow nonnegative price vectors that are not strictly positive. For instance, let $u(x, y) = x + \sqrt{y}$, and $p = (0, 1)$. Then $(1, 0)$ minimizes $p \cdot (x, y)$ over \mathbf{R}_+^2 subject to $u(x, y) \geq 1$ as $p \cdot (1, 0) = 0$, but it does not maximize u subject to $p \cdot (x, y) \leq 0$, since $u(x, 0) = x$ and $p \cdot (x, 0) = 0$ for all x .

Expenditure minimization

Let $\hat{x}(p, v)$ minimize $p \cdot x$ subject to $u(x) - v = 0$, so that \hat{x} minimizes the cost of achieving utility level v . The Lagrangean for this is

$$p \cdot x - \mu(u(x) - v)$$

and by the Lagrange Multiplier Theorem first-order conditions are (multiplying by -1)

$$p_i - \hat{\mu} u_i(\hat{x}) = 0 \quad i = 1, \dots, n,$$

and the second-order conditions for a minimum are

$$-\sum_i \sum_j u_{ij}(\hat{x}) v_i v_j \geq 0 \quad \text{for all } v \text{ such that } \sum_i u_i(\hat{x}) v_i = 0.$$

Again assumption U.3 guarantees the second-order conditions are satisfied, and that the Jacobian of the system is nonsingular.

Differentiate each of the first-order conditions with respect to p_j to get

$$\delta_{ij} - \hat{\mu} \sum_k u_{ik} \frac{\partial \hat{x}_k}{\partial p_j} - \frac{\partial \hat{\mu}}{\partial p_j} u_i = 0 \quad \begin{array}{l} i = 1, \dots, n, \\ j = 1, \dots, n \end{array}$$

or, dividing by $\hat{\mu}$,

$$\sum_k u_{ik} \frac{\partial \hat{x}_k}{\partial p_j} + \frac{\partial \hat{\mu}}{\partial p_j} \frac{u_i}{\hat{\mu}} = \frac{\delta_{ij}}{\hat{\mu}} \quad \begin{array}{l} i = 1, \dots, n, \\ j = 1, \dots, n. \end{array}$$

Differentiating with respect to v to get

$$-\hat{\mu} \sum_k u_{ik} \frac{\partial \hat{x}_k}{\partial v} - \frac{\partial \hat{\mu}}{\partial v} u_i = 0 \quad i = 1, \dots, n.$$

or, dividing by $-\hat{\mu}$,

$$\sum_k u_{ik} \frac{\partial \hat{x}_k}{\partial v} + \frac{\partial \hat{\mu}}{\partial v} \frac{u_i}{\hat{\mu}} = 0 \quad i = 1, \dots, n.$$

Now take the constraint $u(\hat{x}) - v = 0$, and differentiate with respect to p_j to get

$$\sum_k u_k \frac{\partial \hat{x}_k}{\partial p_j} = 0 \quad j = 1, \dots, n,$$

so $\sum_k \frac{\partial \hat{x}_k}{\partial p_j} \frac{u_i}{\hat{\mu}} = 0$, and differentiate with respect to v to get

$$\sum_i u_i \frac{\partial \hat{x}_i}{\partial v} - 1 = 0.$$

Arranging in matrix terms gives

$$\begin{bmatrix} u_{11} & \dots & u_{1n} & \frac{1}{\hat{\mu}} u_1 \\ \vdots & & \vdots & \vdots \\ u_{n1} & \dots & u_{nn} & \frac{1}{\hat{\mu}} u_n \\ \frac{1}{\hat{\mu}} u_1 & \dots & \frac{1}{\hat{\mu}} u_n & 0 \end{bmatrix} \begin{bmatrix} \frac{\partial \hat{x}_1}{\partial p_1} & \dots & \frac{\partial \hat{x}_1}{\partial p_n} & \frac{\partial \hat{x}_1}{\partial v} \\ \vdots & & \vdots & \vdots \\ \frac{\partial \hat{x}_n}{\partial p_1} & \dots & \frac{\partial \hat{x}_n}{\partial p_n} & \frac{\partial \hat{x}_n}{\partial v} \\ \frac{\partial \hat{\mu}}{\partial p_1} & \dots & \frac{\partial \hat{\mu}}{\partial p_n} & \frac{\partial \hat{\mu}}{\partial v} \end{bmatrix} = \begin{bmatrix} \frac{1}{\hat{\mu}} & 0 & 0 \\ & \ddots & \vdots \\ 0 & \frac{1}{\hat{\mu}} & 0 \\ \hline 0 & \dots & 0 & \frac{1}{\hat{\mu}} \end{bmatrix}$$

Once again, let's rearrange things to get

$$\begin{bmatrix} \frac{\partial x_1^*}{\partial p_1} & \dots & \frac{\partial x_1^*}{\partial p_n} & \frac{\partial x_1^*}{\partial v} \\ \vdots & & \vdots & \vdots \\ \frac{\partial x_n^*}{\partial p_1} & \dots & \frac{\partial x_n^*}{\partial p_n} & \frac{\partial x_n^*}{\partial v} \\ \frac{1}{\mu^*} \frac{\partial \mu^*}{\partial p_1} & \dots & \frac{1}{\mu^*} \frac{\partial \mu^*}{\partial p_n} & \frac{1}{\mu^*} \frac{\partial \mu^*}{\partial v} \end{bmatrix} = \frac{1}{\hat{\mu}} \begin{bmatrix} u_{11} & \dots & u_{1n} & u_1 \\ \vdots & & \vdots & \vdots \\ u_{n1} & \dots & u_{nn} & u_n \\ u_1 & \dots & u_n & 0 \end{bmatrix}^{-1}.$$

We know from our results on matrices negative definite under constraint that the matrix

$$\begin{bmatrix} \frac{\partial \hat{x}_1}{\partial p_1} & \dots & \frac{\partial \hat{x}_1}{\partial p_n} \\ \vdots & & \vdots \\ \frac{\partial \hat{x}_n}{\partial p_1} & \dots & \frac{\partial \hat{x}_n}{\partial p_n} \end{bmatrix}$$

is negative semidefinite of rank $n - 1$. Consequently, for each i ,

$$\frac{\partial \hat{x}_i}{\partial p_i} \leq 0.$$

Moreover we also know that the null space of this matrix is the one-dimensional linear space spanned by $u'(\hat{x})$.

Combining the two

Look at equivalent expenditure minimization and utility maximization problems. That is, set $v = u(x^*(p, m))$. Then

$$x^*(p, m) = \hat{x}(p, v) \quad \text{and} \quad \lambda^* = \frac{1}{\hat{\mu}}.$$

Thus we have just shown in (7) that

$$\frac{\partial x_i^*}{\partial p_j} = \frac{\partial \hat{x}_i}{\partial p_j} - x_j^* \frac{\partial x_i^*}{\partial m},$$

a formula known as the **Slutsky decomposition**.

Now define the **expenditure function**

$$e(p, v) = p \cdot \hat{x}(p, v),$$

and observe that

$$\frac{\partial e}{\partial p_j} = \sum_{i=1}^n p_i \frac{\partial \hat{x}_i}{\partial p_j} + \hat{x}_j.$$

Now cleverly notice that

$$\begin{bmatrix} \frac{\partial \hat{x}_1}{\partial p_1} & \cdots & \frac{\partial \hat{x}_1}{\partial p_n} \\ \vdots & & \vdots \\ \frac{\partial \hat{x}_n}{\partial p_1} & \cdots & \frac{\partial \hat{x}_n}{\partial p_n} \end{bmatrix} \begin{bmatrix} p_1 \\ \vdots \\ p_n \end{bmatrix} = 0$$

since $p = \hat{\mu} u'(\hat{x})$ is in the null space. Thus,

$$\frac{\partial e(p, v)}{\partial p_j} = \hat{x}_j(p, v).$$

Also, defining the **indirect utility function**

$$v(p, m) = u(x^*(p, m)),$$

we have

$$\frac{\partial v}{\partial p_j} = \sum_{i=1}^n u_i \frac{\partial x_i^*}{\partial p_j} = \sum_{i=1}^n \lambda^* p_i \frac{\partial x_i^*}{\partial p_j},$$

and

$$\frac{\partial v}{\partial m} = \sum_{i=1}^n u_i \frac{\partial x_i^*}{\partial m} = \sum_{i=1}^n \lambda^* p_i \frac{\partial x_i^*}{\partial m} = \lambda^*.$$

Therefore

$$\begin{aligned}\frac{\frac{\partial v}{\partial p_j}}{\frac{\partial v}{\partial m}} &= \sum_{i=1}^n \lambda^* p_i \frac{\partial x_i^*}{\partial p_j} \\ &= \sum_{i=1}^n \lambda^* p_i \left(\frac{\partial \hat{x}_i}{\partial p_j} - x_j^* \frac{\partial x_i^*}{\partial m} \right) \\ &= \sum_{i=1}^n \lambda^* p_i \frac{\partial \hat{x}_i}{\partial p_j} - x_j^* \sum_{i=1}^n \lambda^* p_i \frac{\partial x_i^*}{\partial m} \\ &= 0 - x_j^* \cdot (1).\end{aligned}$$

Which gives us **Roy's Law**:

$$x_j^* = - \frac{\frac{\partial v}{\partial p_j}}{\frac{\partial v}{\partial m}}.$$