## Envelope theory for constrained optimization

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Envelope theory shows us how to deal with the interplay of direct and indirect effects of parameters in a constrained maximization (or minimization) problem:

Consider the following problem:
Choose $x$ to maximize (or minimize) $f(x, a)$ subject to the constraint that $g(x, a) \leq b$. where $x$ is an $n$ vector, $a$ is an $m$ vector, and $b$ is a scalar. Think of $a, b$ as a vector of "parameters" for the problem, $x$ as a "choice vector" and $f$ as a payoff function. Assume that $f$ and $g$ are twice continuously differentiable functions and that a unique maximum exists $x(a, b)=\left(x_{1}(a, b) \ldots x_{n}(a, b)\right.$ exists for all $a$ and $b$ in in some open set.

To avoid complications, let us assume that $f$ and $g$ are both strictly increasing functions of $x .^{1}$

Define $v(a, b)=f(x(a, b))$. The $v(a, b)$ is the maximum payoff attained with the parameters $a, b$. We know from earlier considerations that at a maximum, it must be that for some scalar, $\lambda$, and for all $i=1, \ldots n$,

$$
\begin{equation*}
\frac{\partial f(x(a, b), a)}{\partial x_{i}}=\lambda \frac{\partial g(x(a, b), a)}{\partial x_{i}} \tag{1}
\end{equation*}
$$

and also that for all $a$ and $b$ in the domain,

$$
\begin{equation*}
g(x(a, b))=b \tag{2}
\end{equation*}
$$

Since Equation 2 holds for all $b$, the derivative of the left side equals that of the right side, so we must have

$$
\begin{equation*}
\sum_{i} \frac{\partial g(x(a, b), a)}{\partial x_{i}} \frac{\partial x_{i}(a, b)}{\partial b}=1 \tag{3}
\end{equation*}
$$

Similarly, since Equation 2 holds for all $a$, it must be that for every $j=1, \ldots m$, the derivative of the left side with respect to $a_{j}$ is equal to that of the right side. This tells us that

$$
\begin{equation*}
\sum_{i} \frac{\partial g(x(a, b), a)}{\partial x_{i}} \frac{\partial x_{i}(a, b)}{\partial a_{j}}+\frac{\partial g(x(a, b), a)}{\partial a_{j}}=0 \tag{4}
\end{equation*}
$$

Now we know that

$$
\begin{equation*}
v(a, b)=f(x(a, b), a) \tag{5}
\end{equation*}
$$

Lets see what we can learn about the derivatives of $v$. First we have

$$
\begin{align*}
\frac{\partial v(a, b)}{\partial b} & =\frac{\partial f(x(a, b), a)}{\partial b}  \tag{6}\\
& =\sum_{i} \frac{\partial f(x(a, b), a)}{\partial x_{i}} \frac{\partial x_{i}(a, b)}{\partial b} \tag{7}
\end{align*}
$$

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$$
\begin{align*}
& =\lambda \sum_{i} \frac{\partial g(x(a, b), a)}{\partial x_{i}} \frac{\partial x_{i}(a, b)}{\partial b}  \tag{8}\\
& =\lambda \tag{9}
\end{align*}
$$
\]

where the step from Equation 7 to Equation 8 follows from Equation 1 and the step from 8 to 9 follows from Equation 3 .

Next let us take derivatives with respect to $a_{k}$. We have

$$
\begin{align*}
\frac{\partial v(a, b)}{\partial a_{k}} & =\frac{d f(x(a, b), a)}{d a_{k}}  \tag{10}\\
& =\sum_{i} \frac{\partial f(x(a, b), a)}{\partial x_{i}} \frac{\partial x_{i}(a, b)}{\partial a_{k}}+\frac{\partial f(x(a, b), a)}{\partial a_{k}}  \tag{11}\\
& =\lambda \sum_{i} \frac{\partial g(x(a, b), a)}{\partial a_{k}} \frac{\partial x_{i}(a, b)}{\partial a_{k}}+\frac{\partial f(x(a, b), a)}{\partial a_{k}}  \tag{12}\\
& =-\lambda \frac{\partial g(x(a, b), a)}{\partial a_{k}}+\frac{\partial f(x(a, b), a)}{\partial a_{k}}  \tag{13}\\
& =-\frac{\partial v(a, b)}{\partial b} \frac{\partial g(x(a, b), a)}{\partial a_{k}}+\frac{\partial f(x(a, b), a)}{\partial a_{k}} \tag{14}
\end{align*}
$$

So we have

$$
\begin{equation*}
\frac{\partial v(a, b)}{\partial a_{k}}=-\frac{\partial v(a, b)}{\partial b} \frac{\partial g(x(a, b), a)}{\partial a_{k}}+\frac{\partial f(x(a, b), a)}{\partial a_{k}} . \tag{15}
\end{equation*}
$$

Why is this interesting? Notice that Equation 15 involves only the derivatives of the function $v$ and the "direct" effects of the parameter $a_{k}$ on the payoff function and on the constraint function. It doesn't involve any terms that relate to the indirect effects of changes in the $x_{i}$ 's. If the functional form of the direct effects is fairly simple, we can make useful inferences.

Let us consider two familiar examples.
Example 1: The standard consumer budget problem. In this case we interpret $x$ be a vector of $n$ commodities, $a$ as a vector of $n$ prices and $b$ as income. Then in our earlier notation, $f(x, a)=u(x)$ and $g(x, a)=\sum a_{i} x_{i}$ and $x(a, b)$ is the demand vector that maximizes $u(x)$ subject to $p x \leq b$. In this case, we see that

$$
\frac{\partial f(x, a)}{\partial a_{k}}=0
$$

for all $k$. (Consumers don't care directly about prices, but only about how they affect their budgets.) We also see that

$$
\frac{\partial g(x(a, b), a)}{\partial a_{k}}=x_{k}(a, b)
$$

Therefore the equation 15 tells us that

$$
\frac{\partial v(a, b)}{\partial a_{k}}=-\frac{\partial v(a, b)}{\partial b} x_{k}(a, b)
$$

which if let $p=a$ and $m=b$ implies that

$$
x_{k}(p, m)=-\frac{\partial v(p, m)}{\partial p_{k}} \div \frac{\partial v(p, m)}{\partial m}
$$

and so we are able to find the Marshallian demand functions just by taking partial derivatives of the indirect utility function.

Example 2: Cost minimization problem Again, let $x$ be a vector of $n$ commodities, $a$ as a vector of $n$ prices and $b$ as income. This time, let $f(x, a)=$ $\sum_{i} a_{i} x_{i}$, let $b$ represent a specified utility level $u$ and let $g(x, a)=u(x)$. Then $x(a, b)$ is the solution to the constrained minimization problem Minimize $f(x, a)$ subject $g(x, a)=b$. The value of the solution $v(a, b)$ is this time the "expenditure function"' $e(p, u)$ where $e(p, u)$ is the cost of achieving utility $u$ at prices $p$.

This time the direct effects are

$$
\frac{\partial f(x(a, b), a)}{\partial a_{k}}=x_{k}(a, b)
$$

and

$$
\frac{\partial g(x(a, b), a)}{\partial a_{k}}=0
$$

So when we apply Equation 15, we have

$$
\begin{align*}
\frac{\partial e(p, u)}{\partial p_{k}} & =\frac{\partial e(p, u)}{\partial u} \times 0+x_{k}(p, u)  \tag{16}\\
& =x_{k}(p, u) \tag{17}
\end{align*}
$$

The solution $x(p, u)$ to this problem is known as the "Hicksian demand function" and the function $x_{k}(p, u)$ is the Hicksian demand for good $k$.


[^0]:    ${ }^{1}$ This assumption can be greatly relaxed.

