## Economics 671

Solutions: Problem Set \#1
(1) First, let's expand the traditional formula. Note that

$$
\sum_{i}\left(x_{i}-\bar{x}\right)\left(y_{i}-\bar{y}\right)=\sum_{i} x_{i} y_{i}-n \overline{x y}=\sum_{i} x_{i} y_{i}-\frac{1}{n}\left(\sum_{i} x_{i}\right)\left(\sum_{i} y_{i}\right) .
$$

Likewise, for the denominator:

$$
\sum_{i}\left(x_{i}-\bar{x}\right)^{2}=\sum_{i} x_{i}^{2}-n \bar{x}^{2}=\sum_{i} x_{i}^{2}-\frac{1}{n}\left(\sum_{i} x_{i}\right)^{2}
$$

Multiplying each of these by $n$, it follows that the traditional formula for the OLS slope estimator is equivalent to:

$$
\hat{\beta}_{2}=\frac{n \sum_{i} x_{i} y_{i}-\left(\sum_{i} x_{i}\right)\left(\sum_{i} y_{i}\right)}{n \sum_{i} x_{i}^{2}-\left(\sum_{i} x_{i}\right)^{2}} .
$$

Now, direct application of our $\left(X^{\prime} X\right)^{-1} X^{\prime} y$ formula gives:

$$
\hat{\beta}=\left[\begin{array}{cc}
n & \sum_{i} x_{i} \\
\sum_{i} x_{i} & \sum_{i} x_{i}^{2}
\end{array}\right]^{-1}\left[\begin{array}{c}
\sum_{i} y_{i} \\
\sum_{i} x_{i} y_{i}
\end{array}\right] .
$$

Inverting the $2 \times 2$ matrix and picking of the second element of $\hat{\beta}$ shows that

$$
\hat{\beta}_{2}=\frac{n \sum_{i} x_{i} y_{i}-\left(\sum_{i} x_{i}\right)\left(\sum_{i} y_{i}\right)}{n \sum_{i} x_{i}^{2}-\left(\sum_{i} x_{i}\right)^{2}}
$$

which is the same as the above.
(2a) To accomplish this, first define $A$ as a $k \times k$ matrix that permutes the columns of $X$. The matrix $A$ will take the form that each row of $A$ will contain only one 1 , and all other entries will be zero. Similarly, each column of $A$ will contain only one 1 , and all the other elements will be zero.

Just to provide a specific example, suppose that $X$ is an $n \times 3$ matrix. And, let $A$ be defined as follows:

$$
A=\left[\begin{array}{lll}
0 & 1 & 0 \\
0 & 0 & 1 \\
1 & 0 & 0
\end{array}\right] .
$$

If we let

$$
Z=X A
$$

it follows that $Z$ is simply an $n \times 3$ matrix that puts the third column of $X$ as the first column of $Z$, the first column of $X$ as the second column of $Z$, and the second column of $X$ as the third column of $Z$. So, $A$ is constructed to simply permute the column order of $X$ in this particular way. This generalizes beyond the three-variable case and $A$ can be constructed to accomplish column rearranging of any desired sort. Finally, note that, however constructed,

$$
A A^{\prime}=A^{\prime} A=I_{k}
$$

so that $A^{-1}=A^{\prime}$. Now, let us consider the OLS estimator of a regression of $y$ on $Z$ and call this estimator $\hat{\theta}$ :

$$
\begin{aligned}
\hat{\theta} & =\left(Z^{\prime} Z\right)^{-1} Z^{\prime} y \\
& =\left([X A]^{\prime}[X A]\right)^{-1}[X A]^{\prime} y \\
& =\left(A^{\prime}\left(X^{\prime} X\right) A\right)^{-1} A^{\prime} X^{\prime} y \\
& =A^{-1}\left(X^{\prime} X\right)^{-1}\left(A^{\prime}\right)^{-1} A^{\prime} X^{\prime} y \\
& =A^{-1}\left(X^{\prime} X\right)^{-1} X^{\prime} y \\
& =A^{\prime} \hat{\beta}
\end{aligned}
$$

This also implies

$$
A \hat{\theta}=\hat{\beta},
$$

where $\hat{\beta}$ is the OLS estimator of a regression of $X$ on $y$. Thus, the OLS estimator produced when rearranging the columns of $X$ is simply a rearrangement of the initial OLS estimates.
(2b) No, this does not violate the rank condition. $r$ and $x$ will be correalted typically, but this construction does not imply that any one of the coumns of the $X$ matrix can be expressed as a linear combination of the other columns of $X$.
(2c) This follows similarly to (2a) with the construction

$$
A=\left[\begin{array}{llll}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 1 & 1 & 0 \\
0 & 0 & 0 & 1
\end{array}\right]
$$

where it follows that

$$
A^{-1}=\left[\begin{array}{cccc}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & -1 & 1 & 0 \\
0 & 0 & 0 & 1
\end{array}\right] .
$$

Thus, if we stack our first regression into a $n \times 4$ matrix $X$ and the second regression into an $n \times 4$ matrix $Z$, and apply the same result as was described in (2a), we have

$$
\hat{\pi}=A^{-1} \hat{\beta}
$$

or

$$
\left[\begin{array}{l}
\hat{\pi}_{0} \\
\hat{\pi}_{1} \\
\hat{\pi}_{2} \\
\hat{\pi}_{3}
\end{array}\right]=\left[\begin{array}{cccc}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & -1 & 1 & 0 \\
0 & 0 & 0 & 1
\end{array}\right]\left[\begin{array}{l}
\hat{\beta}_{0} \\
\hat{\beta}_{1} \\
\hat{\beta}_{2} \\
\hat{\beta}_{3}
\end{array}\right]=\left[\begin{array}{c}
\hat{\beta}_{0} \\
\hat{\beta}_{1} \\
\hat{\beta}_{2}-\hat{\beta}_{1} \\
\hat{\beta}_{3}
\end{array}\right] .
$$

This makes sense since, upon subbing $w_{i}=r_{i}-x_{i}$, we get

$$
\begin{aligned}
y_{i} & =\beta_{0}+\beta_{1}\left(r_{i}-x_{i}\right)+\beta_{2} x_{i}+\beta_{3} z_{i}+u_{i} \\
& =\beta_{0}+\beta_{1} r_{i}+\left(\beta_{2}-\beta_{1}\right) x_{i}+\beta_{3} z_{i}+u_{i}
\end{aligned}
$$

This substituion gives the same relationship between the coefficients $\beta$ and $\pi$ as suggested among the estimates $\hat{\pi}$ and $\hat{\beta}$ above.

