## Supplementary Materials

## Theorem:

The aggregate GSV measure aggrGSV $=n \cdot(\bar{y}-f(\overline{\mathbf{x}}))$ indicates the sum of profit efficiencies of the firms in group I at the most favorable non-negative input prices. Specifically:

$$
\operatorname{aggr}^{\sin } V_{I}=\max _{\mathbf{w} \geq 0} \sum_{i=1}^{n}\left(\left(y_{i}-\mathbf{w}^{\prime} \mathbf{x}_{i}\right)-\pi(\mathbf{w})\right) .
$$

## Proof:

Starting from the average profit inefficiency stated on the right-hand side of the equation posited in the Theorem, we can reorganize the expression as:

$$
\begin{align*}
& \max _{\mathbf{w} \geq 0} \sum_{i=1}^{n}\left(\left(y_{i}-\mathbf{w}^{\prime} \mathbf{x}_{i}\right)-\pi(\mathbf{w})\right)  \tag{A1}\\
& =n \cdot \max _{\mathbf{w} \geq 0}\left(\sum_{i=1}^{n} y_{i} / n-\sum_{i=1}^{n} \mathbf{w}^{\prime}\left(\mathbf{x}_{i} / n\right)-\pi(\mathbf{w})\right)  \tag{A2}\\
& =n \cdot \max _{\mathbf{w} \geq 0}\left(\bar{y}-\mathbf{w}^{\prime} \overline{\mathbf{x}}-\pi(\mathbf{w})\right)  \tag{A3}\\
& =n \cdot\left(\bar{y}-\min _{\mathbf{w} \geq 0}\left(\mathbf{w}^{\prime} \overline{\mathbf{x}}+\pi(\mathbf{w})\right)\right) . \tag{A4}
\end{align*}
$$

Regarding the minimization problem, note that the cost of the average input vector (i.e., $\mathbf{w}^{\prime} \overline{\mathbf{x}}$ ) increases as the input prices $\mathbf{w}$ increase, whereas the profit function $\pi(\mathbf{w})$ is a decreasing function of $\mathbf{w}$. Since $f$ is concave, $\pi(\mathbf{w})$ is convex, and thus the minimization problem has a unique global optimum.

Differentiating $\left(\mathbf{w}^{\prime} \overline{\mathbf{x}}+\pi(\mathbf{w})\right)$ with respect to input prices $\mathbf{w}$, we have the first-order conditions:

$$
\begin{equation*}
\overline{\mathbf{x}}+\nabla \pi(\mathbf{w})=0 \tag{A5}
\end{equation*}
$$

where $\nabla \pi(\mathbf{w})$ is the subgradient of the profit function at $\mathbf{w}$. If $f$ is differentiable, then the subgradient reduces to the gradient vector:

$$
\nabla \pi(\mathbf{w})=\left(\begin{array}{cc}
\frac{\partial \pi(\mathbf{w})}{\partial w_{1}} \cdots & \partial \pi(\mathbf{w}) \\
& \partial w_{R}
\end{array}\right)^{\prime}
$$

By Hotelling's lemma (Hotelling 1932):

$$
\nabla \pi(\mathbf{w})=\left(\begin{array}{c}
-x_{1}^{*}(\mathbf{w})  \tag{A6}\\
\vdots \\
-x_{R}^{*}(\mathbf{w})
\end{array}\right) \quad \quad^{*}(\mathbf{w}),
$$

where $\mathbf{x}^{*}(\mathbf{w})$ is the optimal profit maximizing input vector at prices $\mathbf{w}$.
Hotelling's lemma can also be established for non-differentiable functions by using the sub-gradients (see e.g., Blume 2008 for details). In that case, $\mathbf{x}^{*}(\mathbf{w})$ is not unique, but it does not influence the optimal solution to the minimization problem in (A4).

Inserting the right-hand side of (A6) to equality (A5), we have the first-order condition:

$$
\begin{equation*}
\overline{\mathbf{x}}-\mathbf{x}^{*}(\mathbf{w})=0 . \tag{A7}
\end{equation*}
$$

Therefore, the optimal solution to the minimization problem of (A4) can be expressed as:

$$
\begin{equation*}
\min _{\mathbf{w} \geq 0}\left(\mathbf{w}^{\prime} \overline{\mathbf{x}}+\pi(\mathbf{w})\right)=\mathbf{w}^{\prime} \overline{\mathbf{x}}+\left(f(\overline{\mathbf{x}})-\mathbf{w}^{\prime} \overline{\mathbf{x}}\right)=f(\overline{\mathbf{x}}) . \tag{A8}
\end{equation*}
$$

Inserting the last expression of (A8) back to (A4), we have:

$$
\begin{equation*}
\max _{\mathbf{w} \geq 0}\left(\sum\left(y_{i}-\mathbf{w}^{\prime} \mathbf{x}_{i}\right)-\pi(\mathbf{w})\right)=n \cdot(\bar{y}-f(\overline{\mathbf{x}}))=\operatorname{aggrGSV}_{I} . \tag{A9}
\end{equation*}
$$

