Energy intensity gap between enterprises and governments: A global perspective

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Abstract. Information asymmetry on energy efficiency target between enterprises and governments is a major controversy about sustainability. Enterprises desire to pursue the maximum profits in the market while governments confront with incomplete information on energy intensity potential and policy implementation. To investigate the influence of information gap between them, this study uses two-tier stochastic frontier (TSF) model with scaling property on the panel data in 56 contracting countries in Kyoto Protocol from 1995 to 2014 on energy intensity from energy, economic and technological perspective. The results present that on average about 70% of the unexplained variations in energy intensity accounts for the influence of energy intensity gap on energy savings potential between enterprises and governments. And the actual energy intensity is upper biased by average 7.03% due to the information asymmetry although the net impacts differ slightly across developing and developed countries and over time. Enterprises have stronger influence on the energy intensity during sample period. We recommend developing countries’ governments to have a strong renewable energy governance framework to support urbanization for economic development is their backbone for long period.

1. Introduction
Climate change has posed the increasingly terrible threats for the earth and human beings with extreme weather and sea level rising, which severely affect human life and the environment [1]. The major reason for the change is that vast amount of greenhouse gases (GHGs) is emitted into the air as a result of consuming energy. Global cooperation to mitigate GHGs emission originated from Kyoto Protocol in 2005. But with the economic growth around the world, energy consumption has increased inevitably. It seems that it is contradictory to reduce both GHGs emissions and the energy demand for production. So energy intensity, which is defined as the quantity of energy used for a given level of output, has been concerned for social and environmental sustainability. It is generally measured by energy consumption over Gross Domestic Product (GDP) at a macro level [2]. The low value denotes a lower cost of converting energy into output with less GHGs emissions. Not only governments have strived for GHGs emissions reduction by making and revising relevant policies, but enterprises also should carry out them. But enterprises might confront with the cost of energy intensity policies, energy management inefficiency, energy prices and other uncertainties [3]. Therefore, the energy intensity gap between enterprises and governments has chiefly affected the energy target setting and implementation.
2. Literature review
Many studies have focused on energy intensity in literature. First, the determinants of energy intensity were analyzed at the state or regional level. The roles of trade openness, technology, energy price, population, globalization and economic growth were examined to reduce energy intensity [1][4]. Second, both positive and negative effects of energy intensity were found because they depended on the development patterns of different countries [5][6]. Third, energy intensity gap was investigated and it was suggested that activity correction effect was introduced to bridge the gap [7][8]. The comparison of energy intensity in most studies was made among different countries and seldom between enterprises and governments. But the energy targets of governments depend on enterprises’ actions. Because governments cannot supervise all the processes of energy conversation, the effects cannot be confirmed. And the benefits from investments on energy access by enterprises are unpredictable. All these leads to the asymmetric information between enterprises and governments, which causes the inefficiency of energy intensity target [3].

The contributions of this paper are as follows. First, most researches have little-studied the comparison of energy intensity gap between enterprise and governments involving single country, such as China [3]. This study adds to the literature with the information on energy intensity gap for developing and developed countries. Second, some important factors can be learned from the application of TSF model [9] for the effect of incomplete information between enterprises and governments on energy intensity from the energy, economic and technological factors at the global level. The TSF model links two sided noises, and thus specifically appropriate to explore the reason of information asymmetry on both sides of the energy intensity market, with surpluses that enterprises and governments can extract. Relying on the opposite impacts of both sides, the net impact will make the actual energy intensity higher or lower than the expected level. This study has significant suggestions for the future policymaking in energy intensity target, which not only reveals the potential of energy intensity improvement across countries, but also further narrow the gap between enterprises and governments.

3. Data and methodology
Fifty-six countries were chosen and classified as developing and developed countries in Kyoto Protocol, based on data availability for the period from 1995 to 2014. Energy intensity was regarded as explained variable since it was influenced by incomplete information between enterprises and governments. And the differences in worldwide energy intensity could be determined by other variables in Table 1.

| Variables                      | Measurement            | Notation | Mean   | SD   | Min  | Max   |
|-------------------------------|------------------------|----------|--------|------|------|-------|
| Energy intensity              | MJ/$2011 PPP GDP       | ln(enin) | 1.67   | 0.18 | 0.69 | 3.28  |
| Renewable energy consumption  | % of total final energy consumption | renew | 20.38  | 33.08| 0.44 | 83.18 |
| GDP per capita                | constant 2010 US$      | lngdp   | 9.17   | 1.64 | 6.13 | 11.42 |
| Urban population              | % of total population  | upop    | 65.13  | 34.65| 18.20| 97.83 |
| Mobile cellular subscriptions | per 100 people         | ln(mob) | 3.24   | 4.32 | -8.04| 5.20  |
| Trade Openness                | % of GDP               | open    | 73.70  | 49.28| 15.64| 220.41|
| Financial Development Index   |                         | fd      | 0.46   | 0.05 | 0.03 | 1     |
| D1=0 for developing countries | Dummy                  | D1      | 0.5    | 0.25 | 0    | 1     |
| D2=0 for 1995-2004, D2=1 for 2005-2014 | Dummy | D2    | 0.5    | 0.25 | 0    | 1     |
Renewable energy consumption captured the change of energy intensity resulting from energy mix. GDP per capita and trade openness as public information were selected to reflect the influence of social and economic development on the energy intensity improvement over time. Urban population and Financial Development Index were regarded as the administrative management to carry out the environmental and energy policies. Mobile cellular subscriptions were considered as the technological force enabling energy intensity to improve. All data were collected from World Bank and International Monetary Fund. The data of energy intensity, GDP per capita and mobile cellular subscriptions were logged using natural logarithm. The dummies were included for countries and years.

TSF model was advanced by Kumbhakar and Parmeter [9] and Parmeter [10]. The model was initially applied to evaluate the influence of informational inefficiencies on transaction price between two parties. In this study, the explained variable $EI_i$ is the expected energy intensity, which has both lower and upper unobservable bounds. The actual energy intensity is influenced by enterprises and governments who have asymmetrical information on energy saving target. According to Kumbhakar and Parmeter [9][10], the TSF model can be written with a stochastic noise term for the $i$th observation $(i=1,\ldots, n)$ as follows:

$$E I_i = x_i \beta + \varepsilon_i$$

(1)

where $\beta$ is the parameter vector to be estimated, $x_i$ is a vector of covariates, and $\varepsilon_i$ is the composite error term. $\varepsilon_i$ contains one non-negative error term, $\omega_i = (1-\eta)[EI_i - \mu(x)'] \geq 0$, the other non-negative, $u_i = \eta[\mu(x') - EI_i] \geq 0$, and the third one $v_i$ as a zero-mean symmetric random disturbance, where $EI_i$ denotes the lowest energy intensity if governments adopt all policies to reduce energy intensity, $EI_i$ means the highest energy intensity without any constraints from governments, $\eta (0 \leq \eta \leq 1)$is the coefficient evaluating the governments’ intervention, and $\mu(x') = EI_i - \eta[EI_i - EI]$ is the governments’ target of energy intensity depending on their information and policies; $\eta[EI_i - EI]$ shows the governments’ influence on the energy intensity by their stringent policy options, for example, related laws. To identify the surplus of enterprises and governments, the expected energy intensity in information asymmetry, $\mu(x)$, can be rewritten as

$$\mu(x) = EI_i - \eta[EI_i - EI] = \mu(x)^* + (1-\eta)[EI_i - \mu(x)^*] - \eta[\mu(x)^* - EI]$$

(2)

where $(1-\eta)[EI_i - \mu(x)^*]$ is surplus of enterprises, and $\eta[\mu(x)^* - EI]$ is surplus of governments.

Thus, our empirical model is as below:

$$E I_i = x_i \beta + \omega_i - u_i + v_i,$$

(3)

where $u_i$ shows that governments seek to reduce energy intensity by policy intervention, and $\omega_i$ reveals enterprises’ influence to make energy intensity upper biased.

In TSF model, we will estimate $\beta$, $\omega_i$ and $u_i$ using the maximum likelihood method on the basis of the following distributional assumptions of the error terms. Both $\omega_i$ and $u_i$ are assumed to be independent and identically distributed exponential distributions, meaning $\omega_i \sim \text{i. i. d.} \text{Exp}(\sigma_{\omega}, \sigma_{\omega}^2)$ and $u_i \sim \text{i. i. d.} \text{Exp}(\sigma_u, \sigma_u^2)$, and $v_i$ follows a normal distribution, $v_i \sim \text{i. i. d.} \text{Exp}(\sigma_v, \sigma_v^2)$, where $\sigma^2$s are variations of corresponding error terms. And we also assume $\omega_i, u_i$ and $v_i$ are distributed independently of each other and from the regressors $x_i$. Then the probability density function $f(\cdot)$ of the error term $\varepsilon_i$ can be obtained as follows (the derivation in details see Kumbhakar and Parmeter [9]):

$$f(\varepsilon_i) = \frac{\exp(s_i)}{\sigma_u + \sigma_\omega} \Phi(p_i) + \frac{\exp(t_i)}{\sigma_u + \sigma_\omega} \Phi(q_i),$$

(4)

where $s_i = \frac{\sigma_{\omega}^2}{2\sigma_u} + \frac{\varepsilon_i}{\sigma_u}, t_i = \frac{\sigma_{\omega}^2}{2\sigma_\omega} - \frac{\varepsilon_i}{\sigma_\omega}, p_i = -\frac{\varepsilon_i}{\sigma_u} - \frac{\sigma_u}{\sigma_\omega}, q_i = \frac{\varepsilon_i}{\sigma_\omega} - \frac{\sigma_u}{\sigma_\omega}$, and $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution. The log likelihood function for a sample of $n$ observations can be

$$\ln L(x; \beta, \sigma_\omega, \sigma_u, \sigma_v) = -n \ln(\sigma_u + \sigma_\omega) + \sum_{i=1}^{n} \ln \left[ e^{s_i} \Phi(p_i) + e^{t_i} \Phi(q_i) \right].$$

(5)

The maximum likelihood estimates of all parameters can be gained by maximizing $\ln L(x; \beta, \sigma_\omega, \sigma_u, \sigma_v)$. It is crucial to notice that all three standard deviations can be identified because the parameters $\sigma_u$ and $\sigma_\omega$ are in the likelihood equations separately, e.g. $\sigma_u$ is in $s_i$ and $p_i$, and $\sigma_\omega$ in $t_i$ and $q_i$. 

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In order to obtain observation-specific estimates of \( u_i \) and \( \omega_i \), we have to further derive the conditional distributions of \( u_i \) and \( \omega_i \), which are expressed as \( f(u_i|\varepsilon_i) \) and \( f(\omega_i|\varepsilon_i) \) as follow, respectively [9]:

\[
\begin{align*}
    f(u_i|\varepsilon_i) &= \frac{\lambda \exp(-\lambda u_i) \Phi(u_i/\sigma_u + q_i)}{\Phi(q_i) + \exp(s_i - t_i) \Phi(p_i)} \\
    f(\omega_i|\varepsilon_i) &= \frac{\lambda \exp(-\lambda \omega_i) \Phi(\omega_i/\sigma_\omega)}{\exp(t_i - s_i) \Phi(q_i) + \exp(s_i - t_i) \Phi(p_i)}
\end{align*}
\]

where \( \lambda = \frac{1}{\sigma_u} + \frac{1}{\sigma_\omega} \). With these conditional distributions we obtain the conditional expectations of \( u_i \) and \( \omega_i \) as following [9],

\[
\begin{align*}
    E(e^{-u_i}|\varepsilon_i) &= \frac{\lambda}{1 + \lambda} \frac{\Phi(q_i) + \exp(s_i - t_i) \Phi(p_i)}{\Phi(q_i) + \exp(s_i - t_i) \Phi(p_i)} \\
    E(e^{-\omega_i}|\varepsilon_i) &= \frac{\lambda}{1 + \lambda} \frac{\Phi(p_i) + \exp(t_i - s_i) \Phi(q_i)}{\Phi(q_i) + \exp(t_i - s_i) \Phi(p_i)}
\end{align*}
\]

We use \( E(e^{-u_i}|\varepsilon_i) \) and \( E(e^{-\omega_i}|\varepsilon_i) \) to derive the observation-specific estimates of \( u_i \) and \( \omega_i \) respectively. The net surplus (\( NS_i \)) of information asymmetry between enterprises and governments can be calculated as:

\[
\begin{align*}
    NS_i &= Surplus \ of \ enterprises - Surplus \ of \ government \\
         &= E(1 - e^{-\omega_i}|\varepsilon_i) - E(1 - e^{-u_i}|\varepsilon_i) = E(\omega_i) - E(u_i)
\end{align*}
\]

If the net impact is positive, the enterprises’ impact dominates. If the net impact is negative, the governments’ impact dominates.

Notice that \( \omega_i \) and \( u_i \) rely on the expected energy intensity under perfect information (\( \mu(x)^{\ast} \)) and the policy intervention parameter (\( \eta_i \)). We anticipate that some variables have some influences on \( \omega_i \) and \( u_i \). In this study, scaling property is introduced to the distributions of both \( u_i \) and \( \omega_i \) to explore the possible influences of some variables in \( x \) on the both one-sided error terms. We have tried to introduce all the variables in \( x \) as scaling variables, i.e., \( u_i = e^{\delta_i(x)} u_i^\ast \) and \( \omega_i = e^{\delta_i(x)} \omega_i^\ast \), where \( \omega_i^\ast \) and \( u_i^\ast \) are independent and identically exponential distributed and the distributions of \( \omega_i \) and \( u_i \) are scaled by a non-negative related to some variables in \( x \). The covariates are tried one by one for \( \omega_i \) and \( u_i \) to find out their important scaling variables. To identify the corresponding effects of \( x \) on both one-sided error terms, we adopt the linear estimation method because the information asymmetry implies that only one covariate can affect the surplus of either enterprises or governments [3]. Therefore, it turns out that technology has certain scaling effect on \( \omega_i \), and trade openness as scaling variables for \( u_i \).

4. Empirical results

Table 2 shows that the result of Model 1 ordinary linear square (OLS) regression implied that all variables except \( fd \) are significant at 5% level. Based on Model 1, the OLS regression is replaced with the traditional TSF model put forward by Kumbhakar and Parmeter [9] to obtain Model 2. Then we seek for scaling variables for each one-sided error term from the covariates in Table 1 to recognize the significant scaling variables. It is shown in model 3 that \( open \) is considered as a scaling variable for the one-sided error term \( u \) for better interpretation of the gap and \( upop \) is not significant. Model 4 displays that only \( inmob \) has the scaling effect on the other error term \( \omega \), which means that enterprises possibly have better information on technology than governments. Thus, in model 5, we remove \( upop \) and try \( open \) and \( inmob \) at the same time. The value of AIC of model 5 is the smallest, so model 5 provides the most optimal estimation for the following analysis.

Renewable energy use, GDP per capita and technology have a significantly negative effect on energy intensity. The estimation is similar to Qi [8]. For a given level of output, the policy for motivating to use renewable energy as a principal driver of economic growth can decrease the energy demand and increase output to lower energy intensity. Meanwhile, energy intensity can be improved at a moderate rate by technical progress. In technically developed countries, energy saving potential may be more cost-effective and capital intensive compared with developing countries, as the coefficient of financial development is significant and negative.
Table 2. Results of estimation.

| Model | 1 OLS | 2 TSF | 3 TSF_υ | 4 TSF_ω | 5 TSF_υω |
|-------|-------|-------|-------|-------|-------|
| renew | -0.006*** | -0.009*** | -0.006*** | -0.007*** | -0.006*** |
|       | (-9.206) | (-11.155) | (-9.409) | (-9.599) | (-9.543) |
| Ingd | -0.243*** | -0.124*** | -0.125*** | -0.187*** | -0.168*** |
|       | (-9.885) | (-4.222) | (-4.812) | (-7.554) | (-6.698) |
| upop | 0.007*** | 0.002 | 0.005*** | 0.005** | 0.005*** |
|       | (6.355) | (1.283) | (3.829) | (4.440) | (4.662) |
| lnmob | -0.038*** | -0.061*** | -0.054*** | -0.133*** | -0.115*** |
|       | (-4.900) | (-6.727) | (-6.862) | (-4.101) | (-4.241) |
| open | 0.003*** | 0.003*** | -0.0004 | 0.002*** | 0.001** |
|       | (8.143) | (8.024) | (-0.458) | (7.830) | (2.224) |
| fd | -0.068 | -0.066 | -0.336*** | -0.168** | -0.278** |
|       | (-0.815) | (-0.720) | (-3.865) | (-2.001) | (-3.258) |
| D1 | 0.305*** | 0.156*** | 0.190*** | 0.249*** | 0.226*** |
|       | (9.871) | (4.262) | (6.024) | (8.027) | (7.320) |
| D2 | -0.064** | -0.078** | -0.015 | -0.091*** | -0.095*** |
|       | (-2.336) | (-2.542) | (-0.525) | (-2.614) | (-2.774) |
| sigma_υ (σ_υ) | | | | | |
| _cons | 0.275*** | 0.341*** | 0.342*** | 0.339*** | |
|       | (12.946) | (45.308) | (46.908) | (46.106) | |
| sigma_u (σ_u) | | | | | |
| upop | 0.004 | | | | |
|       | (0.976) | | | | |
| open | | -0.019*** | | -0.029*** | |
|       | | (-5.078) | | (-4.004) | |
| _cons | 0.141*** | 0.543** | 0.063 | 0.380** | |
|       | (5.966) | (2.135) | (0.021) | (2.296) | |
| sigma_w (σ_w) | | | | | |
| lnmob | | | 0.143*** | 0.177*** | |
|       | | | (4.665) | (4.192) | |
| _cons | 0.240*** | 0.402 | 0.513* | 0.309* | |
|       | (7.402) | (0.096) | (1.935) | (1.716) | |
| AIC | 792.18 | 878.73 | 794.63 | 807.31 | 791.27 |

Note: *, **, *** represent 10%, 5% and 1% significance respectively.

Urbanization and trade openness have significant and positive correlation with energy intensity, although the corresponding coefficients have the smallest absolute value. Our finding is different from Bilgili et al [7]. The plausible reason could be that the urbanization enables people in rural area to raise their living standard and consume modern energy sources for comfortable life, and greater trade openness brings about sufficient supply for households and sectors [1]. For the dummy variables, energy intensity in developed countries is higher than that in developing countries and after 2005 global energy intensity decreases, which proves that Kyoto Protocol is conducive to reducing GHGs emission and improving energy intensity and that developed countries should take more responsibility in addressing climate change.

The coefficients of υ and ω, which show the influence of enterprises and governments, are 0.233 and 0.136, while the coefficient of ν is 0.174, denoting that incomplete information accounts for 70.6% of
the whole variation in energy intensity. In the variation interpreted by information asymmetry, about 74.6% of change in energy intensity is explicated by the enterprises’ influence on energy savings potential, while the rest of 25.4% is attributed to information inefficiency due to the governments’ role.

Table 3 illustrates the mean and standard deviation of surplus of change along with the mean of those at the 25th, 50th and 75th quartiles. The surplus of change in energy intensity extracted by enterprises is higher than by governments. The surplus extracted by governments decreases the energy intensity by 12.02%, while the surplus extracted by enterprises increases the energy intensity by 19.05%. Hence, the net impact of incomplete information between enterprises and governments causes higher energy intensity by 7.03% compared with the expected information symmetry. Moreover, the net effect differs distinctly across countries and years. At the lower quantile, the value of net impact is negative, implying that governments dominate impacts on energy intensity and it is lower than the level without information asymmetry. At the middle and upper quartiles, the net impact rises, indicating that more surplus is extracted by enterprises, with an increase in energy intensity 1.55% and 8.56% of the expected level under perfect information respectively. The similar result was also found in China by Liu et al [3].

Table 3. Surplus of change in energy intensity by enterprises and governments (Unit: %)

|               | Mean | SD  | 25th quantile | 50th quantile | 75th quantile |
|---------------|------|-----|---------------|---------------|---------------|
| Enterprises   | 19.05| 9.16| 11.02         | 13.94         | 18.75         |
| Governments   | 12.02| 3.65| 16.90         | 12.34         | 10.20         |
| Net impact    | 7.03 | 12.01| -5.88         | 1.55          | 8.56          |

Figure 1 displays the average surplus of change in energy intensity extracted by enterprises and governments over time. From 1995 to 2014, enterprises dominated the net impacts, revealing that stronger influence on energy intensity by enterprises, bringing energy intensity higher than the expected level without information asymmetry. The ruling influence of enterprises becomes stronger especially in 2005 and 2010. Since 2005, the net impact began to descend. The reason could be Kyoto Protocol took effect, imposing limits on global emissions of carbon dioxide and other gases.

Figure 1. Surplus of change in energy intensity over 1995-2014.

Table 4. Surplus of change in energy intensity extracted by different countries across periods.

|                | 1995-2004 | 2005-2014 |
|----------------|-----------|-----------|
|                | Enterprise surplus | Government surplus | Net impact | Enterprise surplus | Government surplus | Net impact |
| Developing     | 0.1831    | 0.1337    | 0.0494    | 0.2050    | 0.1156    | 0.0894 |
| Developed      | 0.1890    | 0.1149    | 0.0741    | 0.1848    | 0.1167    | 0.0681 |

We compare the influence of enterprises and governments across the social and economic development and periods, outlined in Table 4. The net impact of information asymmetry of developing countries tends to be twice after 2005 than that of developed countries, implying enterprises in developing countries extract more surplus. The reason could be that enterprises in developing countries prefers to reap the benefits, reluctant to commit to the energy intensity target.
5. Conclusions
This study applies TSF model to explore the impacts of information asymmetry between enterprises and governments on energy intensity in contracting countries in Kyoto Protocol from 1995 and 2014. It is found that about average 70.6% of the unexplained variations accounts for the influence of energy intensity gap on energy intensity potential between enterprises and governments. The mean of net impact indicates that the actual energy intensity is 7.03% higher than the expected level. Particularly enterprises in developing countries have gained more surplus than governments, resulting in an increase in energy intensity above nearly 2% of the mean. Furthermore, the impact of enterprises and governments differs noticeably at the different quartiles. The countries around the world have already taken essential measures to improve energy efficiency by carrying out various policies. This study gives further insights into the impacts of energy intensity gap between enterprises and governments. The current policy in the countries still leave some room to improve the potential of energy intensity. In both developing and developed countries enterprises extracted more surplus, so the important implications on the future policy makings should focus on the policy implementation and information sharing between enterprises and governments. For enterprises, technology is considered important with regard to sustainable policies. For government, encouraging trade openness is conducive to closing the energy intensity gap. We recommend especially developing countries’ governments to have a strong renewable energy governance framework to support urbanization because economic development is their backbone for the long period under consideration. The environmental targets and stringent regulations should be compromised under circumstance of economic growth, technological progress and energy mix to mitigate energy intensity gap and achieve economic sustainability.

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