On decomposing the energy rebound effect*

Yong Tan† Barnabé Walheer‡

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Abstract

We suggest a new decomposition of the rebound effect, highlighting the contribution of four components: efficiency, technology, capital, and energy changes. The new approach offers several advantages: it has a strong economic foundation as it starts from the modelling of the production process, it naturally gives the option to understand how each of the four components contributes to the rebound effect, and it is based on a non-parametric estimation method that does not resort on strong assumptions nor require estimating parameters. We apply our technique to the case of China's logistics industry, which is counteracted by increased energy consumption and carbon emissions to support economic growth. Our findings reveal that the rebound effect varies significantly across provinces, with an average of 0.76. Economic growth, driven by factors such as capital accumulation and technological advancements, plays a crucial role in determining the rebound effect, with provinces experiencing higher growth benefiting from improved energy efficiency. We further establish determinants of the rebound effect, viz., government intervention, environmental control, and economic growth. The results highlight region-specific energy policy that takes note of the spatially heterogeneous impacts of economic development and policy efforts on the rebound effect.

Keywords: Data Envelopment Analysis; rebound effect; efficiency; technology; China.

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†School of Management, University of Bradford, United Kingdom. email: y.tan9@bradford.ac.uk.

‡HEC Liège, Université de Liège, Belgium. email: barnabe.walheer@uliege.be. This work is supported by the Fonds de la Recherche Scientifique (FNRS) under Grant No. J.0193.23. Corresponding author.

1 Introduction

Energy efficiency is one of the cornerstone strategies for mitigating climate change, reducing energy consumption, and fostering sustainable economic growth. However, the energy rebound effect—where improvements in energy efficiency result in less-than-expected reductions in energy consumption due to behavioural or economic responses—poses a significant challenge to realizing the full potential of energy-saving initiatives. The rebound effect has been widely studied across various sectors and regions, with research demonstrating its variability in magnitude, depending on factors such as industry characteristics, geographic contexts, and energy policies (Sorrell and Dimitropoulos, 2008; Sorrell et al., 2009; Madlener and Alcott, 2009; Dimitropoulos et al., 2018).

While the concept of the rebound effect is well understood and its existence is rarely denied, its modelling is much more challenging (Vivanco et al., 2016; Brockway et al., 2021). Several methodologies have been suggested that may be regrouped into two main categories. First, the computable general equilibrium explicitly tries to model the economic agents' responses to energy efficiency shocks (Allan et al., 2007). Such a technique is based on a series of assumptions about the behaviour of the economic agents and the economy (Böhringer and Löschel, 2006). It turns out that the computable general equilibrium allows understanding the rebound effect mechanisms fully. From a practical point of view, an econometrics model is set, and parameters are estimated using a certain estimation method (Grepperud and Rasmussen, 2004).

Second, the economic accounting approach tries to estimate the rebound effect directly without requesting modelling of the economic agents' behaviour (Lin and Du, 2015). Such an approach starts from the definition of the rebound effect and highlights the importance of specific dimensions to the rebound effect, such as technological change, efficiency change, input change, and scale efficiency change (Stern, 2020). Over time, the economic accounting approach has gained popularity because it is easier to use, less sensitive to assumptions, and does not require estimating parameters (Egan and Schaltegger, 2023). Shortcomings of the economic accounting approach are that it is usually focused on one or a few dimensions and that it does not start from an economic model. In a sense, it might give the impression that the economic accounting approach is sometimes used to highlight the contribution of specific dimensions while ignoring other potential channels, without any solid economic foundation.

Building on these drawbacks, we suggest, in this paper, a new economic accounting approach that it based on a production function framework and that highlights the contribution of four dimensions: technological change, efficiency change, capital accumulation, and energy accumulation. The new approach gives an intuitive and complete decomposition of the rebound effect while being based on a standard economic model. That is, our approach is directly connected with both the computable general equilibrium and the economic accounting approaches. As the computable general equilibrium approach, we start with an economic model. As the economic accounting approach, we decompose the rebound effect into different components. All in all, our approach brings the best of the two practices. From an estimating point of view, we rely on a non-parametric approach that does not require making strong assumptions about the production process or estimating parameters.

We apply our new methodology to the rebound effect in China's logistics industry. As a key driver of economic growth and industrial output, the logistics industry plays a crucial role in supporting China's supply chains and infrastructure development. With China's rapid urbanization, industrial expansion, and increasing trade volumes, the logistics sector has seen considerable growth over the past decade. However, this growth has also led to escalating energy consumption and carbon emissions, placing immense pressure on the nation's energy resources and environmental sustainability efforts. Given the scale of China's logistics industry—accounting for a substantial share of national energy use and greenhouse gas emissions—understanding how energy efficiency improvements are offset by the rebound effect is critical for shaping effective energy and environmental policies.

In the logistics industry, the rebound effect would occur as efficiency in energy usage lowers the costs of doing business and therefore causes an increased demand for logistics services. For example, fuel-efficient vehicles, routing systems, or automating warehouse operations can lower per-unit energy usage. Such savings, however, can lead companies to add more delivery volume and service frequency or reduce shipment consolidation, hence increasing total energy consumption. These systemic and behavioral reactions are especially applicable in logistics, where transportation, warehousing, and distribution processes are extremely energy-intensive.

Surprisingly, previous studies have mainly focused their attention on industries such as manufacturing or transportation, neglecting the logistics sector (Berner et al., 2022; Amjadi et al., 2022; Zheng et al., 2022; Liu et al., 2018). We fill this gap by providing a detailed examination of the rebound effect in China's logistics industry. Furthermore, we provide an in-depth regional analysis, exploring the variation in rebound effects across China's provinces. This geographical focus is particularly relevant, given the significant differences in economic development, industrial structure, and energy use across the country. By analyzing regional data, this study sheds light on the localized drivers of the rebound effect, enabling policymakers to design region-specific energy efficiency strategies that account for provincial disparities in energy consumption patterns, regulatory environments, and industrial activity.

Finally, we also explore the determinants of the energy rebound effect, examining factors such as economic level, industrial structure, government input, environmental regulation, and resident consumption levels. By using these determinants in a second-stage analysis, this study provides actionable insights for policymakers and industry leaders to design more effective energy policies that account for the rebound effect and its underlying drivers. A distinguished feature of our second-stage analysis is that our decomposition allows us to better understand how the determinants impact certain aspects of the rebound effect.

Our paper is structured as follows. We present a literature review in Section 2 and expose our methodology in Section 3. We run our empirical application in Section 4. There, we give the results for the rebound effect for China's logistics industry, and present its decomposition. We also run a second-stage analysis to better understand our results. We conclude in Section 5.

2 Literature review and empirical context

We first present recent studies about the rebound effect. This allows us to explain recent findings and give some figures. Then, we focus our attention on our empirical context: the Chinese logistics sector.

2.1 Literature review

The rebound effect has been extensively analyzed through various methodologies. Adetutu et al. (2016) employed a two-stage dynamic panel data method and stochastic frontier analysis (SFA) to estimate the economy-wide rebound effects across 55 countries. Their results indicate that, in the short run, a 100% energy efficiency improvement is followed by a 90% rebound in energy consumption, but in the long run, it leads to a 136% decrease in consumption. Similarly, Amjadi et al. (2018) analyzed four energy-intensive sectors in Sweden—pulp and paper, basic iron and steel, chemical, and mining—using firm-level panel data and SFA. Their findings suggest that fuel and electricity rebound effects do not fully offset potential energy and emission savings. Moreover, CO_2 emissions and fuel/electricity share were found to have significant impacts on the size of the rebound effect.

In the residential sector, Aydin et al. (2017) investigated 563,000 Dutch households using instrumental variables and fixed-effects models to address endogeneity concerns. The rebound effect was 26.7% among homeowners and 41.3% among tenants. The study also documented substantial heterogeneity in the rebound effect, showing that wealthier households experience a smaller rebound, with the lowest wealth quantile experiencing around 40%, while the highest wealth quantile saw only 19%. The effect was also higher for lower-income households (49%) and those with higher gas consumption for heating. Belaid et al. (2020), using a quantile regression model, explored the direct rebound effect in a survey of 2,356 French households. They reported a rebound effect ranging from 72% to 86%, with heterogeneity among consumption quantiles.

Bohringer and Rivers (2021) utilized a general equilibrium model to estimate the rebound effect, decomposing it into partial and general equilibrium components. They concluded that both components could be substantial. Similarly, Borenstein (2015) presented a microeconomic framework to disentangle the rebound effect into income and substitution effects, finding that rebound is unlikely to offset energy savings but reduces net savings by 10%-40%. Chitnis and Sorrell (2015) estimated the price and expenditure elasticities of household goods and services to evaluate the CO_2 emissions of these goods. Their findings showed rebound effects of 41% for domestic gas efficiency, 48% for electricity, and 78% for vehicle fuel, largely driven by substitution effects.

Borger et al. (2016) focused on the rebound effect in Denmark's car transport sector using household-level data. By addressing endogeneity through an instrumental variable approach, they estimated the rebound effect to be between 7.5% and 10%, with no significant income effect. Dimitropoulos et al. (2018) conducted a meta-analysis of 74 studies and 1,120 estimates of the rebound effect in road transport, finding that long-run rebound effects are generally larger than short-run ones, contrasting with Adetutu et al. (2016). Their analysis also revealed that rebound effects decline over time, with lower per capita incomes, higher gasoline prices, and higher population density associated with larger effects.

Galvin (2015) contributed to the rebound literature by exploring the ICT and electronics sectors. The study identified structural changes caused by energy efficiency improvements in ICT and electronics, leading to increased device usage and energy consumption, with rebound effects ranging from 115% to 161%. Ghosh and Blackhurst (2014) expanded on previous research by proposing the concept of efficiency correlation to explain how multiple simultaneous efficiency improvements across services might produce large rebound effects. Their model simulations suggested that these effects could be as substantial as traditional direct and indirect rebounds.

Hediger et al. (2018) analyzed direct and indirect rebound effects in residential heating using a choice experiment. The average direct rebound was found to be 12%, while the indirect rebound was 24%, combining for a total rebound of about 33%. The study identified significant heterogeneity in rebound effects, with income, education, and ownership status explaining much of the variation. Ventilation was identified as the most popular behavioral adaptation. At the macro level, Koesler et al. (2016) extended the analysis of 'economy-wide' rebound effects by including international spill-over effects using a global computable general equilibrium model. They found that 10% energy efficiency improvements in Germany's manufacturing sector were associated with global rebound values of 48.11%, suggesting significant global consequences.

2.2 Empirical context

In China, Chai et al. (2016) estimated the rebound effects in the road transport sector using a system of simultaneous equations. Their findings revealed that rebound effects increased along with income, a result in contrast with Aydin et al. (2017), due to differing country contexts and methodologies. The study also found that short-run rebound effects are larger than long-run ones, consistent with Adetutu et al. (2016). Lin and Du (2015), measuring the rebound effect in the Chinese economy from 1981 to 2011, found that rebound effects ranged from 30% to 40%.

Liu et al. (2019) proposed an improved approach to estimating the direct rebound effect in Chinese industry by decomposing it into substitution and output channels.

The direct rebound effect was found to be 37%, with the substitution channel contributing 13.1% and the output channel 23.9%. Lu et al. (2017), using a computate general equilibrium model, found that rebound effects varied by energy type in China, with primary energy goods exhibiting larger effects than secondary goods. Wen et al. (2018) examined the carbon rebound effect and rebound risk across provinces, finding significant differences, with Xinjiang, Qinghai, and Ningxia being the most vulnerable. Yan et al. (2019) estimated the rebound effect across 30 Chinese provinces, showing an average of 88.55% in the short run and 77.50% in the long run, with a decreasing trend in developed eastern provinces and increasing rebound in western regions. Zhang et al. (2017) provided aggregate and disaggregate analyses of China's industrial sector, finding an energy rebound effect ranging from 20% to 76% (or 39% on average) between 1995 and 2012. The rebound effect in manufacturing was relatively smaller, averaging 28%. Overall, their study documented a decreasing trend in energy rebound effects over time.

Recent research has kept advancing the understanding of energy efficiency improvement and how it affects energy consumption trends, particularly in China's logistics and transportation industry. Zha et al. (2023) investigated the direct energy rebound effect (ERE) of road transport in China through panel cointegration and error correction models. Both their road freight and passenger transport evidence display partial rebound effects (long run: 13%-48% and short run: 3.9%-41%), meaning that efficiency gain does not switch into saving energy, further to find evidence supporting asymmetric price effects when rising fuel price doesn't fall into using energy. It makes China's transportation consumption complex to change its habit of behavior to consuming energy less. These observations are particularly relevant to the logistics industry, whose freight transport patterns play a decisive role in aggregate energy demand.

At the same time, Guo et al. (2024) explored the function of green finance and technological innovation in promoting low-carbon development within China's logistics sector. With panel data for 30 provinces (2005–2019), their research finds that green finance and technological innovation are conducive to low-carbon development but are subject to industrial structure and environmental regulation. They suggest a regional and phased development strategy with the proviso that policy-specific interventions are required. Their findings make the argument for policy-based mechanisms being able to prevent energy rebound effects by promoting sustainable technology adoption and regulation.

Recent studies have extensively studied the rebound effect in China's high-tech energy-intensive industries using high-resolution data and high-tech empirical methods. Liang et al. (2022) also investigated the rebound effect of China's logistics technological innovation by utilizing a dynamic spatial Durbin model on 30 provinces from 2002 to 2019. According to their findings, there exists an apparent spatial rebound effect with the average being 60.61%, regional heterogeneity, and spatial spillovers that strengthen the rebound effect, while optimization of the energy structure has an inhibitory impact. Augmenting this, Zhou et al. (2022) presented firm-level estimates of China's manufacturing sector energy rebound effect, with rebound magnitudes across subsectors varying from 43.2% to 96.8%. This study addresses micro-level heterogeneity and shows that reaction to gains in efficiency is not uniform across industries or places.

In addition, Bai et al. (2024) gave a focused analysis of the carbon rebound effect of technological change in China's transport industry. Using a nonparametric frontier approach, they estimated rebound rates at the provincial level between 2006 and 2021 and found that the average CRE was 69.19% and that there were stronger rebound effects in the western provinces compared to the eastern provinces. These results underscore rebound effects' sectoral and spatial heterogeneity and again emphasize that regional heterogeneity must be taken into consideration when making policies.

Tan et al. (2025) introduce a variable coefficient production function to measure China's energy rebound effect (ERE), addressing limitations in traditional methods that assume constant output elasticities. Using total-factor energy productivity instead of energy intensity, they find an average ERE of 27.21%, lower than the 30.43% estimated by a Cobb-Douglas model, which tends to overestimate the effect. Their study highlights regional and sectoral disparities, with the tertiary and secondary industries experiencing the highest rebound effects due to expanding energy demand. By offering a more dynamic, data-driven approach, their findings provide valuable insights for refining China's energy efficiency policies.

Our research makes a significant contribution to the existing literature on the rebound effect by addressing key gaps and advancing both methodology and empirical understanding. While much of the prior research has focused on industries like manufacturing, transport, and residential energy use, the current study shifts the focus to China's logistics sector, an under-explored yet critical driver of economic growth and energy consumption. This sector's significance in China's economy, coupled with its substantial energy demands, offers a new context for understanding the rebound effect, which has been largely neglected in prior work. Additionally, the introduction of a novel economic accounting approach, rooted in a production function framework, offers a more comprehensive definition and decomposition of the rebound effect than previous methods, which have often been constrained by limited assumptions or narrowly defined dimensions. Furthermore, using a second-stage analysis, we identify the key determinants of the rebound effect and its decomposition. This enhances the understanding of its drivers in China's logistics industry.

3 Methodology

Our starting point is the observation of inputs used to generate an output for a panel dataset of entities between two time periods, labelled b and c.[1] As a preliminary step, we explain how we define the production process. Next, we define the rebound effect and show how it can be decomposed into four parts: the contribution of efficiency change, technological change, capital accumulation, and energy accumulation. Finally, we show how the decomposition components can be computed non-parametrically.

3.1 Defining the technology

We consider that each entity uses capital K, labour L and energy E to generate output Y. We model the technology using a production function. First, the production function must fulfil certain properties to remain coherent with macroeconomic standards (Kumar and Russell, 2002; Henderson and Russell, 2005; Walheer, 2016, 2021, 2024; Chambers and Pieralli, 2020). In particular, we assume that it is quasi-concave, monotone, and homogeneous of degree one (i.e. constant returns-to-scale).[2] Next, we recognize that technological progress (or regress) may occur over time. Finally, we acknowledge the potential inability of entities to convert inputs into output (Debreu, 1951; Farrell, 1957). This results in a difference between actual and potential outputs.

[1] Note that our methodology also works in the case of multiple outputs. We consider the single output setting here as it is the one used in our empirical application in Section 4.

[2] Such assumptions can be dropped or changed if needed. Using the produce explained in Walheer (2019b), we can confirm that constant returns-to-scale holds for our empirical context.

All in all, we obtain for every entity

$$y_t = f_t(k_t, e_t) - \eta_t, \tag{1}$$

where $y_t = Y_t/L_t$, $k_t = K_t/L_t$, and $e_t = E_t/L_t$ are output, capital, and energy per unit of labour, respectively. Note that here we use the homogeneity of degree one assumption to rewrite the production function per labour term.[3] For the moment, this rewriting might seem usefulness but it will ease our presentation of the rebound effect definition and decomposition in the next sections.

$f_t(k_t, e_t)$ is the time-varying production function at time t, and therefore represents the potential output. As it varies with t, it implies that technological change is possible over time. The difference between actual and potential outputs is captured by $\eta_t = f_t(k_t, e_t) - y_t$, which can be interpreted as an (in)efficiency component reflecting the inability to properly convert inputs into output using a certain technology. The benchmark value is zero meaning that $f_t(k_t, e_t) = y_t$. When it is larger than zero: $f_t(k_t, e_t) > y_t$, revealing an inefficiency behaviour and thus a potential output gain. In practice, both $f_t(k_t, e_t)$ and η_t are unobserved. Finally, note that it might be surprising that no error term appears in (1), this feature will be discussed in Section 3.4.

3.2 Defining the rebound effect

As explained in the literature review in Section 2, there are several ways to define the rebound effect: in terms of elasticity, price, potential values, etc. In a production context, defining the rebound effect in terms of outputs and inputs is more coherent (Vivanco et al., 2016). In particular, two differences are at the core of the production-based definition: $y_c - y_b$ and $EI_b - EI_c$ where EI_t denotes the energy intensity of period t. First, $y_c - y_b$ captures the output per worker change between periods b and c, that is economic development. We expect such a difference to be positive. Note that using output per worker is fairer than using output as entities may have different sizes. Also, we prefer normalizing using workers rather than the full population since the former takes the market conditions into account. Next, $EI_b - EI_c$ measures the

[3]The production function is defined as $Y_t = F_t(L_t, K_t, E_t) - \nu_t$. By dividing the entire equation by L_t, we obtain: $Y_t/L_t = F_t(L_t, K_t, E_t)/L_t - \nu_t/L_t$, which is equivalent to $y_t = F_t(1, k_t, e_t) - \nu_t/L_t$. By defining $f_t(k_t, e_t) = F_t(1, k_t, e_t)$ and $\eta_t = \nu_t/L_t$, we find equation (1).

energy intensity change. When an entity is less energy-intensive over time, such a difference is positive. Otherwise, it is negative.

At this point, it is fair to note that it is not uncommon to use such two differences to define the rebound effect (e.g. Li and al., 2016; Wu et al., 2018; Jin and Kim, 2019; Miao and Chen, 2022; Omondi et al., 2023). The main contrast with our approach is that we combine our economic model defined in Section 3.1 and the rebound effect definition to end with a simple and intuitive four-part decomposition of the rebound effect.

Based on our two differences, we can define the rebound effect between periods b and c as follows:

$$RE = \frac{(y_c - y_b)EI_b}{y_c(EI_b - EI_c)}. \tag{2}$$

Intuitively, at the top we find the extra energy needed to support economic development between periods b and c, and at the bottom, the energy saving due to economic development between the same periods. The rebound effect has no unit and can take positive and negative values. First, in case of no economic growth between periods b and c, we obtain that $RE = 0$. Next, as EI_b and y_c take by construction positive values, the sign of the rebound effect is determined only by the two differences $y_c - y_b$ and $EI_b - EI_c$. It is less likely that $y_c - y_b < 0$ as this would mean that economic growth is negative between b and c. However, $EI_b - EI_c < 0$ is possible and implies that the entity is more energy-intensive over time. It turns out that a negative rebound effect generally implies that the entity is more energy-intensive to support economic development. On the contrary, when the rebound effect is positive, it means that we have both economic development and a less energy-intensive entity. We summarize the interpretations of the rebound effect values in Table 1.

3.3 Decomposing the rebound effect

Different reasons may explain the value of the rebound effect. Following the previous works exposed in Section 2, we keep four main elements. First, the ability of the entity to convert the inputs into output, i.e. the efficiency change. Next, technological change, i.e. how the entities innovate over time. The third factor is the impact of capital, and the last one is the impact of energy. We explain how to obtain such four components from the initial definition of the rebound effect in (2) by using different

Table 1: Rebound effect interpretation

	$y_c - y_b > 0$	$y_c - y_b = 0$	$y_c - y_b < 0$
$EI_b - EI_c > 0$	$RE > 0$ positive economic growth less energy-intensive	$RE = 0$ no economic growth less energy-intensive	$RE < 0$ negative economic growth less energy-intensive
$EI_b - EI_c = 0$	impossible	impossible	impossible
$EI_b - EI_c < 0$	$RE < 0$ positive economic growth more energy-intensive	$RE = 0$ no economic growth more energy-intensive	$RE > 0$ negative economic growth more energy-intensive

versions of the production function in (1).

First, by plugging our definition of the production function in (1) at times b and c in our definition of the rebound effect as defined in (2), we obtain the following:

$$\frac{(y_c - y_b)EI_b}{y_c(EI_b - EI_c)} = \frac{[(f_c(k_c, e_c) - \eta_c) - (f_b(k_b, e_b) - \eta_b)]EI_b}{y_c(EI_b - EI_c)}, \tag{3}$$

$$= \frac{[(\eta_b - \eta_c) + (f_c(k_c, e_c) - f_b(k_b, e_b))]EI_b}{y_c(EI_b - EI_c)}. \tag{4}$$

On the left-hand side, we have RE: the rebound effect between b and c. On the right-hand side, we have two factors: the first is the contribution of (in)efficiency change between b and c, i.e. $EFF = \frac{(\eta_b - \eta_c)EI_b}{y_c(EI_b - EI_c)}$, while the second factor has no clear meaning (for the moment). We can thus rewrite (4) as follows:

$$RE = EFF + \frac{[f_c(k_c, e_c) - f_b(k_b, e_b)]EI_b}{y_c(EI_b - EI_c)}. \tag{5}$$

Next to make the contribution of technological change to the rebound effect appear, we notice that there are two ways to define technological change in our context:

$$TECH_c = \frac{[f_c(k_c, e_c) - f_b(k_c, e_c)]EI_b}{y_c(EI_b - EI_c)}, \tag{6}$$

$$TECH_b = \frac{[f_c(k_b, e_b) - f_b(k_b, e_b)]EI_b}{y_c(EI_b - EI_c)}. \tag{7}$$

Both indexes measure technological change but generally do not yield the same results.[4] To aggregate both indexes, a simple procedure is to take an average (Caves

[4]The two decompositions are equal only if the neutrality of technological change is assumed.

et al., 1982; Luenberger, 1992, 1995; Fare et al., 1993; Chambers et al., 1998). Such an approach is commonly used in the literature, and in related empirical contexts (Kumar and Russell, 2002; Henderson and Russell, 2005; Walheer, 2016, 2021; Chambers and Pieralli, 2020). In a sense, it avoids creating a path dependence when decomposing the rebound effect. In our case, we take the arithmetic average of the two indexes in (6) and (7):

$$TECH = \frac{1}{2}\left[TECH_c + TECH_b\right]. \tag{8}$$

Next, we plug our definition of the contribution of technological change in (8) in (5):

$$RE = EFF + TECH + \frac{1}{2}\left[\frac{[f_c(k_c,e_c) - f_c(k_b,e_b)]EI_b}{y_c(EI_b - EI_c)} + \frac{[f_b(k_c,e_c) - f_b(k_b,e_b)]EI_b}{y_c(EI_b - EI_c)}\right]. \tag{9}$$

The two last terms in (9) will be used to obtain our last two factors: the contribution of capital accumulation ($KACC$) and the contribution of energy accumulation ($EACC$).

Let us start with the first term: $\frac{[f_c(k_c,e_c)-f_c(k_b,e_b)]EI_b}{y_c(EI_b-EI_c)}$. It can be decomposed in two different manners highlighting the impact of one specific variable:

$$\begin{aligned}
\frac{[f_c(k_c,e_c) - f_c(k_b,e_b)]EI_b}{y_c(EI_b - EI_c)} &= \frac{[f_c(k_c,e_c) - f_c(k_b,e_c)]EI_b}{y_c(EI_b - EI_c)} + \frac{[f_c(k_b,e_c) - f_c(k_b,e_b)]EI_b}{y_c(EI_b - EI_c)}, \\
&= KACC_c(e_c) + EACC_c(k_b). && (10) \\
\frac{[f_c(k_c,e_c) - f_c(k_b,e_b)]EI_b}{y_c(EI_b - EI_c)} &= \frac{[f_c(k_c,e_c) - f_c(k_c,e_b)]EI_b}{y_c(EI_b - EI_c)} + \frac{[f_c(k_c,e_b) - f_c(k_b,e_b)]EI_b}{y_c(EI_b - EI_c)}, \\
&= KACC_c(e_c) + EACC_c(k_b). && (11)
\end{aligned}$$

Next, we apply the same procedure to the second factor in (9), i.e. $\frac{(f_b(s_c,u_c)-f_b(s_b,u_b))EI_b}{y_c(EI_b-EI_c)}$:

$$\begin{aligned}\frac{[f_b(k_c,e_c)-f_b(k_b,e_b)]EI_b}{y_c(EI_b-EI_c)} &= \frac{[f_b(k_c,e_c)-f_b(k_b,e_c)]EI_b}{y_c(EI_b-EI_c)}+\frac{[f_b(k_b,e_c)-f_b(k_b,e_b)]EI_b}{y_c(EI_b-EI_c)}, \\ &= KACC_b(e_c)+EACC_b(k_b), \qquad (12)\\ \frac{[f_b(k_c,e_c)-f_b(k_b,e_b)]EI_b}{y_c(EI_b-EI_c)} &= \frac{[f_b(k_c,e_c)-f_b(k_c,e_b)]EI_b}{y_c(EI_b-EI_c)}+\frac{[f_b(k_c,e_b)-f_b(k_b,e_b)]EI_b}{y_c(EI_b-EI_c)}, \\ &= KACC_b(e_c)+EACC_b(k_b). \qquad (13)\end{aligned}$$

The different components in (10)–(13) highlight the contribution of capital or energy accumulation to the rebound effect. These components are path-dependent as they depend on a specific time period. Following the spirit of our definition of $TECH$ in (8), we define the path-independent contributions of capital and energy accumulation to the rebound effect as follows:

$$KACC = \frac{1}{4}\left[KACC_b(u_b)+KACC_b(u_c)+KACC_c(u_b)+KACC_c(u_c)\right]. \qquad (14)$$

$$EACC = \frac{1}{4}\left[EACC_b(s_b)+EACC_b(s_c)+EACC_c(s_b)+EACC_c(s_c)\right]. \qquad (15)$$

Note that, this time, we divide by four (and not by two as in (8)) because there are four different ways to define the contribution of capital and energy to the rebound effect (see (10)–(13)). This last step ends our decomposition of the rebound effect into four factors:

$$RE = EFF + TECH + KACC + EACC. \qquad (16)$$

Each component highlights the contribution of one specific dimension and gives us the option to better understand the patterns found for the rebound effect between periods b and c. As explained in Section 3.2, the rebound effect can take a positive or a negative value. It turns out that the same applies to the four components. When a component is positive (negative), it means that such a component contributes positively (negatively) to the rebound effect. Note that it is possible to consider a combination of components (see our discussion of Table 4). The interpretations of the four factors are summarized in Table 2. To obtain a full picture, it is important to first understand why the rebound effect is positive or negative (see Table 1).

In practice, several production functions have to be estimated to obtain the de-

Table 2: Rebound effect decomposition factors

factor	interpretation
EFF	movement toward (> 0) or away (< 0) from the best practice
$TECH$	technological progress (> 0) or regress (< 0)
$KACC$	positive (> 0) or negative (< 0) impact of physical capital per labor deepening
$EACC$	positive (> 0) or negative (< 0) impact of energy per labor accumulation

composition. Some of them are even counterfactual as they involve several periods. The computational aspect is the topic of the next section.

3.4 Estimation

To estimate the different components defined previously, we make use of a non-parametric linear programming technique: Data Envelopment Analysis (DEA; Charnes et al., 1972). The basic principle is to compute the potential outputs using other entities as peers such that the production functions fulfil the properties imposed (here: monotonicity, quasi-concavity and homogeneity of degree one). An important aspect is that linear programming has to be defined in a general manner as counterfactual concepts have to be computed.

We remark that a disadvantage of using linear programming is that measurement errors and potential outliers are ignored. To mitigate this shortcut, we adopt the well-known order-m estimator to compute the potential outputs (Daraio and Simar, 2007; Walheer, 2019a). The basic principle is to compute B times expected potential outputs obtained with random sub-samples of m peers.[5]

The linear programming for entity i evaluated at (y_{ib}, k_{ib}, e_{ib}) with respect to sub-

[5]In our application, we set $B = 1,000$, and $m = 10$.

sample h of m peers in period c (denoted $S_c^h(m)$) is given as follows:

$$
\begin{aligned}
\hat{f}_c^h(y_{ib}, k_{ib}, e_{ib}) = \max_{y \geq 0; \forall s: \lambda_s \geq 0} & \; y \\
& \text{(C-1) } y \leq \sum_{s \in S_c^h(m)} \lambda_s y_{sc}, \text{for} \\
& \text{(C-2) } k_{ib} \geq \sum_{s \in S_c^h(m)} \lambda_s k_{sc}, \\
& \text{(C-3) } e_{ib} \geq \sum_{s \in S_c^h(m)} \lambda_s e_{sc}, \\
& \text{(C-4) } 1 \geq \sum_{s \in S_c^h(m)} \lambda_s.
\end{aligned} \tag{17}
$$

The linear programming has to be solved for each entity.[6] Once the linear programmings are solved B times, i.e. one time for each sub-sample h, we can obtain the expected production function for each entity i:

$$\hat{f}_c(y_{ib}, k_{ib}, e_{ib}) = \mathbb{E}[\hat{f}_c^h(y_{ib}, k_{ib}, e_{ib})] \tag{19}$$

The estimated efficiency scores are easily obtained using (1). All estimated concepts have to be interpreted as their theoretical counterpart.

[6]We remark that the linear programming in (17) can equivalently be rewritten as follows:

$$
\begin{aligned}
\hat{F}_c^h(Y_{ib}, L_{ib}, K_{ib}, E_{ib}) = \max_{Y \geq 0; \forall s: \mu_s \geq 0} & \; Y \\
& \text{(C-1) } Y \leq \sum_{s \in S_c^h(m)} \mu_s Y_{sc}, \text{for} \\
& \text{(C-2) } K_{ib} \geq \sum_{s \in S_c^h(m)} \mu_s K_{sc}, \\
& \text{(C-3) } E_{ib} \geq \sum_{s \in S_c^h(m)} \mu_s E_{sc}, \\
& \text{(C-3) } L_{ib} \geq \sum_{s \in S_c^h(m)} \mu_s L_{sc}.
\end{aligned} \tag{18}
$$

We obtain the equivalence between both linear programming by dividing each side of all inequalities by L_{ib} and by defining $\lambda_s = \mu_s \frac{L_{sc}}{L_{ib}}$ for all s.

4 Application

This study addresses a research gap by investigating the energy rebound effect in China's logistics industry across 31 provinces between 2011 and 2020. We estimate and decompose the rebound effect using the methodology explained in Section 3. We start by explaining how we get the data and then discuss our results. We end our empirical application with a second-stage analysis that helps to understand better the patterns found for the rebound effect and its decomposition.

4.1 Data and preliminary results

We make use of a setting with one output and three inputs for 31 Chinese provinces between 2011–2020. The inputs are labour, capital, and energy, while the output is the added value. By doing this, we follow the common practice in the literature when studying the logistics industry (see Table 7 in the Appendix). Note that we prefer added value over pure output as the former takes quantities and prices into account. This is fairer when comparing provinces over time. The data sources for our four variables are fourfold: 1) National Bureau of Statistics of China; 2) China Statistical Yearbook; 3) China Energy Statistical Yearbook, and 4) provincial and municipal development bulletins.

The number of employees is an essential input as it reflects the human resources involved in the logistics industry (Holl and Mariotti, 2018). The number of employees correlates with operational capacity, management effectiveness, and productivity, all of which influence overall efficiency. Similarly, investment in fixed assets represents the infrastructure and technology investments made by logistics companies. Higher investments typically indicate better infrastructure and advanced technologies, which can improve operational efficiency and reduce CO_2 emissions (Yao et al., 2022). Furthermore, energy consumption is a direct indicator of the environmental impact of logistics operations. Higher energy consumption typically leads to higher CO_2 emissions, making it a critical input for evaluating emissions efficiency (Yu et al., 2023). Together, these inputs provide a comprehensive view of the resources and operational scale of the logistics industry. On the output side, the value added of the logistics industry quantifies the economic contribution of logistics activities, capturing the value generated through these activities. This measure is crucial for understanding the economic efficiency and overall productivity of the industry (Chen et al., 2024).

Finally, energy intensity is defined as the ratio of total logistics energy consumption to logistics output value. That is, we take a pure output to define energy intensity and not added value. This is more coherent as energy is defined also in quantity terms. This is also in line with the literature, see Table 7 in the Appendix.

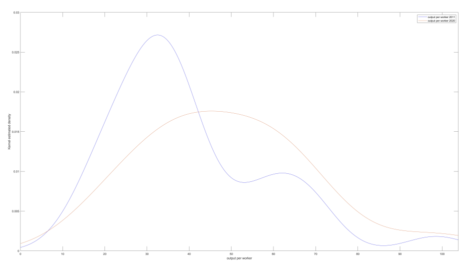
We present the descriptive statistics for the inputs and output in Table 2, and the distributions in Figure 1. Figure 1 presents the distributions of four key variables: (a) output per worker, (b) energy per worker, (c) capital per worker, and (d) energy intensity, providing insights into their variation across the sample.

Table 3: Output and inputs

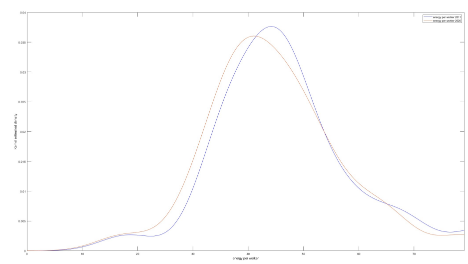
Statistics	added value	energy	capital	energy intensity
unit	10,000 yuan per worker	tons per worker	10,000 yuan per worker	tons per 10,000 yuan
2011				
min	14.47	18.25	9.05	0.45
average	40.06	47.81	48.15	1.39
median	35.06	45.51	41.55	1.25
max	98.57	87.57	247.92	4.16
std	18.92	14.12	40.70	0.70
2020				
min	14.70	17.60	12.62	0.32
average	49.01	44.95	90.14	1.01
median	47.52	44.17	84.19	0.97
max	103.83	87.57	304.02	1.89
std	20.45	12.14	64.51	0.37

In 2011, the added value per worker ranged from a minimum of 14.47 to a maximum of 98.57, with an average of 40.06 (10,000 yuan) per worker. By 2020, output per worker increased slightly, with the minimum at 14.70, the maximum at 103.83, and an average of 49.01. The standard deviation also grew to 20.45, suggesting a widening gap in productivity across provinces compared to 2011. Energy per worker showed a small decline over the period. In 2011, the average was 47.81 tons per worker, while by 2020, the average was 44.95. Capital per worker exhibited significant growth from 2011 to 2020. In 2011, the average was 48.15 (10,000 yuan) per worker, and it rose to 90.14 in 2020. Note also that the standard deviation increases substantially to 64.51, pointing to rising inequality in capital distribution across provinces. Finally,

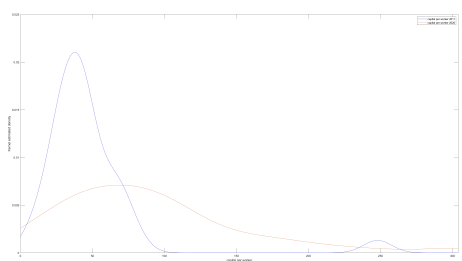
Figure 1: Distributions of Key Production Variables



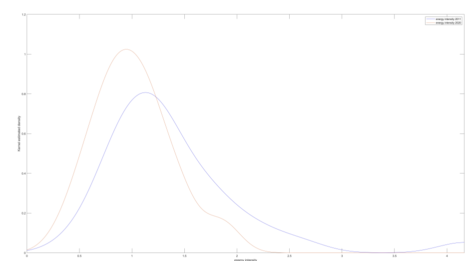
(a) Output per worker



(b) Energy per worker



(c) Capital per worker



(d) Energy intensity

Note: This figure displays the distribution of four core variables used in the translog production function estimation: (a) output per worker, (b) energy per worker, (c) capital per worker, and (d) energy intensity. The charts illustrate the degree of variation across provinces in China's logistics sector from 2011 to 2020.

energy intensity saw a reduction between 2011 and 2020. In 2011, energy intensity ranged from 0.45 to 4.16 tons per 10,000 yuan, with an average of 1.39. By 2020, the minimum dropped to 0.32, the maximum to 1.89, and the average to 1.01. Overall, these changes reflect growth in output and capital per worker, a slight decline in energy usage per worker, and improved energy usage within China's logistics industry between 2011 and 2020.

Figure 1 charts the distribution of several key variables in China's logistics industry. The skew of the output per worker distribution is suggestive that many of the provinces have low output per worker, but some have substantially higher output per worker, and this could be an indication of different industrial development, infrastructure, and technology expenditure. The energy per worker distribution is right-skewed, which implies that some of the provinces use much more energy, which could be indicative of transport intensity, fuel composition, or variation in provincial logistics demand. The distribution of capital per worker also captures increasing differentials of investment, where some of the provinces heavily invest in enhancing their logistics infrastructure while others do not. Finally, energy intensity distribution has a general trend of increasing efficiency, but with a long right tail, suggesting there are still provinces that have energy-intensive logistics activities. These trends indicate China's logistics sector to be diversified and require regional policies to reconcile economic growth and energy efficiency.

4.2 Decomposition results

Using the methodology exposed in Section 3, we compute the rebound effect and its decomposition for the 31 provinces between 2011 and 2020. Results are provided in Table 5 for each province and by using descriptive statistics. We also count the number of provinces with a negative value for each variable. In that table, we also give the results for the two differences $y_c - y_b$ and $EI_b - EI_c$ to ease the interpretation of the rebound effect.

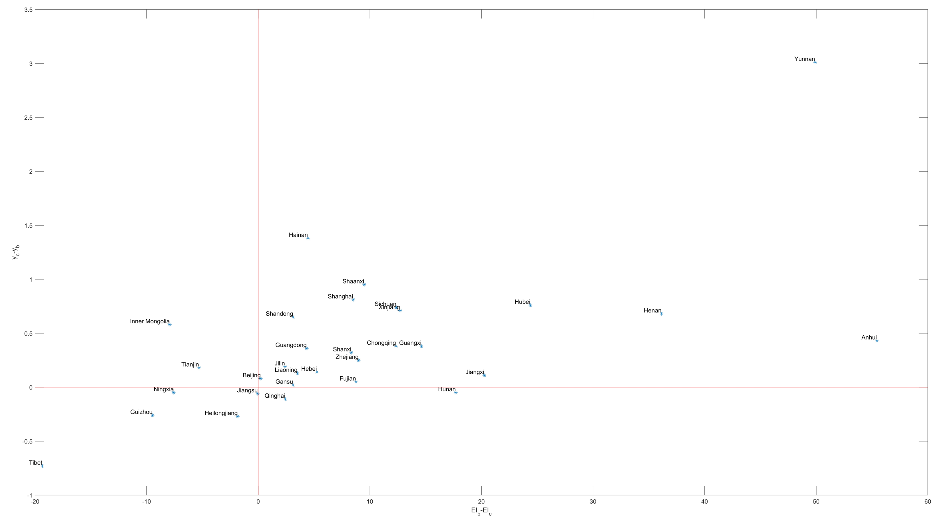
Overall, we see that the rebound effect is positive (average is 0.76 and median is 0.65). Larger rebound effects are found for Gansu (8.02), Jiangxi (3.08), and Fujian (2.34). Gansu shows the immense rebound effect because it has extremely low historical energy efficiency and fast-growing recent industrialization, pushing energy consumption despite enhanced efficiency. The province has been investing heavily in logistics infrastructure to boost trade connectivity, but these investments have translated into higher transport and warehousing activity that raises energy consumption. Jiangxi and Fujian, which have been developing their economies fast and experiencing increasing freight demand, face the same issue. Their logistics industries are expanding due to expanding manufacturing production and trade activity, so growth in demand-driven energy consumption will exceed efficiency gains.

Also, only four provinces have a negative rebound effect (Hunan, Qinghai, Tianjin, and Inner Mongolia). Hunan's strongly negative rebound effect may be due to structural economic changes away from energy-intensive logistics activities. The province has experienced a decline in energy-intensive freight transport due to industrial restructuring and stricter environmental policies. Similarly, Qinghai's negative rebound effect reflects its smaller and less energy-intensive logistics sector. Inner Mongolia, despite being a resource-rich province, has seen limited logistics expansion compared to high-growth coastal regions, allowing energy savings to persist without significant offsetting effects.

To ease our interpretation of the results of the rebound effect, we regroup, in Figure 2, the provinces in four categories using $y_c - y_b$ and $EI_b - EI_c$ as criteria. Following the guidelines explained in Table 1, we notice that two reasons may explain a positive rebound effect. The best-case scenario is when positive economic growth is associated with energy savings. These provinces are situated in the upper right. The worst case is when negative economic growth is associated with more energy consumption. These provinces lie in the lower-left quadrant. The clustering of provinces in the upper-right quadrant indicates that many regions have experienced both economic growth and improved energy efficiency, a sign of good policy action or technological advance. On the other hand, the presence of provinces within the lower-left quadrant, in which economic downturn is combined with rising energy intensity, suggests structural inefficiency or economic stagnation that dissuades sustainable development.

The upper-left quadrant, in which economic development is combined with the rise in energy use, denotes areas for which logistics development remains energy-intensive, possibly due to failure to adopt energy-saving technologies. Finally, the lower-right quadrant comprises provinces that have attained improved energy efficiency at the cost of reduced economic activity, which could demonstrate a scale contraction in logistics activity rather than planned efficiency improvement. This classification elicits the complexity of the rebound effect at the regional level, demanding region-specific

Figure 2: Classification of Provinces by Economic Growth and Energy Intensity Change



Note: Provinces are grouped into four quadrants based on changes in output per worker and energy intensity from 2011 to 2020. The upper-right quadrant reflects provinces achieving both economic growth and energy savings (the best-case rebound scenario), while the lower-left quadrant shows provinces experiencing economic decline with increased energy use (the worst-case scenario). This classification highlights regional differences in energy rebound performance across China's logistics sector.

policy that can maintain economic growth without accepting the excessive consumption of energy.

While we focus on the initial and final period to capture long term patterns, it is possible to compute the rebound effect for each period. Table 8 (in the Appendix) presents the time-varying rebound effect for China's 31 provinces in the period between 2011 and 2020. There are a few notable trends observable from the estimates. To start with, there is profound temporal and spatial heterogeneity in the rebound effect, which features the time-varying energy efficiency offsets. Provincial regions like Jiangxi, Fujian, and Henan always exhibit large rebound effects across some successive years, embodying vigorous responses from the demand side following improved energy efficiency. However, certain provinces like Hunan and Inner Mongolia sometimes show negative rebound effects, which are cases where energy saving was not fully offset by the increase in activity through structural change or logistics growth stagnation. There are some provinces showing a progressive increase in the rebound effect throughout the decade (like Guangdong and Sichuan), while others (like Beijing and Tianjin) remain flat or volatile.

Next, we continue our exploration of the rebound effect in China's logistics industry across 31 provinces between 2011 and 2020 by interpreting the four components of the decomposition: efficiency, technology, capital, and energy changes. We recall that as for the rebound effect, the benchmark value is 0, and that a positive (negative) value implies a positive (negative) contribution to the rebound effect. At the aggregate level, we see a negative contribution of energy accumulation (average -1.59, median -0.54) for 22 provinces. An average negative contribution is also found for efficiency change (-0.12) but this is not confirmed by the median (0.20) and this only concerns 12 provinces. The rebound effect is pushed up by technological change (average 1.17, median 0.48) and capital accumulation (average 1.29, median 0.28).

The energy rebound effect and its components vary widely across provinces. For instance, Tibet (2.53), Qinghai (6.05), and Ningxia (6.62) demonstrate strong positive efficiency changes. This may be due to targeted efforts to improve logistics efficiency and infrastructure investments. Gansu (-16.32) and Hunan (-3.97) exhibit significant negative efficiency changes, which may reflect structural challenges such as lower capital investment levels, slower adoption of modern logistics technologies, or regional disparities in logistics infrastructure development, as suggested by recent studies (e.g., Chen et al., 2024; Liang et al., 2022). In terms of technological advancements, Gansu (28.16) and Liaoning (4.47) show substantial contributions, likely indicating strong innovation efforts in logistics technologies or energy-efficient practices. These regions may have benefited from government policies promoting innovation and industrial upgrades. In contrast, Qinghai (-5.14) and Hunan (-1.71) show negative technological changes, implying either stagnation in innovation or challenges in adopting new technologies. Capital accumulation plays a significant role in Gansu (43.97) and Liaoning (6.36), where substantial capital investments have boosted production capacity and contributed positively to the rebound effect. However, Hunan (-2.69) and Heilongjiang (-3.13) show negative capital accumulation, possibly reflecting disinvestment in capital allocation, further contributing to their negative or low rebound effects. Finally, the extreme values in energy consumption patterns highlight the diverse challenges across regions. For instance, Gansu (-47.79) shows a massive negative energy accumulation, while Qinghai (4.37) shows more moderate positive energy accumulation. These differences underscore the varying impacts of energy consumption trends on the rebound effect.

To better know which component or combinations of components explain the rebound effect patterns, we compute the correlation of coefficients between the rebound effect and each combination of the components.[7] In particular, we consider the four components alone and then group the components two by two and three by three. The correlation of coefficients are provided in Table 4.

Table 4: Correlation of Coefficients Across Decomposition Components

One dimension		Two dimensions		Three dimensions	
EFF	-0.3558	$EFF + TECH$	0.9483	$EFF + TECH + KACC$	0.7904
$TECH$	0.6898	$EFF + KACC$	0.8248	$EFF + TECH + EACC$	-0.5409
$KACC$	0.7020	$EFF + EACC$	-0.6148	$EFF + KACC + EACC$	-0.3996
$EACC$	-0.6968	$TECH + KACC$	0.7032	$TECH + KACC + EACC$	0.6878
		$TECH + EACC$	-0.6234		
		$KACC + EACC$	-0.6968		

Note: This table presents the correlation coefficients among the estimated contributions of the four decomposition components—technological change (TECH), capital accumulation (KACC), energy accumulation (EACC), and efficiency change (EFF). The correlations are calculated based on combinations of these components (individually, in pairs, and in trios) across provinces, providing insight into the consistency and interdependence of their effects on the rebound phenomenon.

When only one dimension is considered, we obtain two positive and two negative coefficients of correlation. Technological change and capital accumulation positively impact the rebound effect, while efficiency change and energy accumulation present a negative impact. Note that these two components have the largest number of provinces with a negative value (see Table 5). Next, with two dimensions, we see that when efficiency and technological changes are combined, we have the highest connection with a correlation coefficient of 0.9483. This implies that these two combined factors are the most important in our empirical case to explain the rebound effect changes. We highlight the positive contribution of efficiency change that remains true when combined with another element. Next, we again find a negative contribution to energy accumulation even when it is combined with another factor. Finally, adding capital accumulation does not improve the connection strengthens but still gives us a positive and strong relationship. Combined factors with energy accumulation show a negative link.

[7]Another option is to compare the distributions (Walheer, 2021). As we obtain very similar conclusions, we do not produce the test results here.

Table 5: Rebound Effect and Decomposition by Province

Province	RE	$y_c - y_b$	$EI_b - EI_c$	EFF	$TECH$	$KACC$	$EACC$
Beijing	0.23	0.23	0.08	-5.27	5.79	6.36	-6.65
Tianjin	-0.40	-5.30	0.18	-0.86	0.48	0.68	-0.70
Hebei	0.17	5.26	0.14	0.17	0.48	0.12	-0.59
Shanxi	0.65	8.34	0.32	-0.09	0.74	-0.57	0.57
Inner Mongolia	-0.32	-7.92	0.58	-0.37	0.19	-0.48	0.34
Liaoning	1.04	3.52	0.13	-2.53	4.47	-4.13	3.23
Jilin	0.46	2.40	0.19	-1.72	1.91	0.88	-0.61
Heilongjiang	0.50	-1.83	-0.27	3.20	-2.73	-3.13	3.16
Shanghai	0.78	8.51	0.81	-0.65	1.35	0.15	-0.07
Jiangsu	0.01	-0.04	-0.06	0.95	-0.67	-1.35	1.09
Zhejiang	0.65	9.00	0.25	0.18	0.66	0.96	-1.14
Anhui	1.37	55.44	0.43	1.14	0.18	0.44	-0.40
Fujian	2.34	8.76	0.05	2.31	0.60	0.00	-0.57
Jiangxi	3.08	20.26	0.11	1.28	1.11	1.54	-0.85
Shandong	0.08	3.13	0.65	-0.05	0.26	0.28	-0.41
Henan	0.92	36.14	0.68	0.63	0.33	0.51	-0.55
Hubei	0.95	24.39	0.76	0.74	0.22	0.53	-0.55
Hunan	-5.89	17.71	-0.05	-3.97	-1.71	-2.69	2.48
Guangdong	0.40	4.35	0.36	-0.72	0.79	1.53	-1.20
Guangxi	1.10	14.63	0.38	0.57	0.49	0.96	-0.91
Hainan	0.28	4.46	1.38	-0.64	0.80	0.66	-0.54
Chongqing	0.99	12.35	0.38	0.40	0.77	0.65	-0.84
Sichuan	0.75	12.39	0.74	0.65	0.23	0.00	-0.13
Guizhou	0.63	-9.46	-0.26	0.71	-0.24	-0.21	0.36
Yunnan	1.04	49.90	3.01	1.04	0.07	0.01	-0.07
Tibet	1.01	-19.34	-0.73	2.53	-1.53	0.04	-0.03
Shaanxi	0.44	9.50	0.95	0.20	0.47	0.71	-0.94
Gansu	8.02	3.13	0.02	-16.32	28.16	43.97	-47.79
Qinghai	-1.66	2.43	-0.11	6.05	-5.14	-6.95	4.37
Ningxia	2.85	-7.57	-0.05	6.62	-2.83	-3.18	2.24
Xinjiang	1.11	12.71	0.71	0.19	0.51	1.84	-1.43
min	*-5.89*	*-19.34*	*-0.73*	*-16.32*	*-5.14*	*-6.95*	*-47.79*
average	*0.76*	*8.95*	*0.38*	*-0.12*	*1.17*	*1.29*	*-1.59*
median	*0.65*	*5.26*	*0.25*	*0.20*	*0.48*	*0.28*	*-0.54*
std	*1.97*	*15.56*	*0.64*	*3.73*	*5.28*	*8.09*	*8.64*
max	*8.02*	*55.44*	*3.01*	*6.62*	*28.16*	*43.97*	*4.37*
$\# < 0$	*4*	*7*	*7*	*12*	*7*	*9*	*22*

Note: RE values and each component (EFF, TECH, KACC, EACC) for all 31 provinces over 2011–2020, plus the variations of y and EI for context. Gansu's extreme RE (8.02) is driven by very large TECH and KACC contributions in a context of low initial efficiency, while Hunan's negative RE (–5.89) stems from strong negative EFF and TECH movements amid structural shifts away from energy intensive logistics.

4.3 Second-stage analysis

We rely on a second-stage analysis to better understand the results of the rebound effect. A distinguished feature of our second-stage analysis is that our decomposition allows us to better understand how the determinants impact certain aspects of the rebound effect. We make use of a regression between the rebound effect or a component and a set of independent variables:

$$Z_i = \beta_0 + \mathbf{X}_i'\boldsymbol{\beta} + u_i, \tag{20}$$

where Z_i is RE, EFF, $TECH$, $KACC$, or $EACC$ of province i. $\mathbf{X}_i$ stands for independent variables for province i that are defined in percentage change over the 2011-2020 period. We do this to be consistent, as the rebound effect has no unit and also captures a change over the same period.

Following the literature and the data availability, we take several determinants of the rebound effect in the logistics industry into account. First, government input in the form of subsidies, infrastructure investments, and policy support can impact the logistics industry's rebound effect. Government initiatives aimed at promoting green logistics and enhancing infrastructure (Li et al., 2021). However, if these improvements lead to lower operational costs, they may also stimulate increased demand for logistics services, potentially triggering a rebound effect (Font Vivanco et al., 2015). Environmental regulation is another critical factor influencing the rebound effect. Stringent environmental regulations can compel logistics companies to adopt cleaner technologies and more efficient practices, reducing overall emissions (Zhu et al., 2013). While environmental regulation is generally expected to reduce emissions, in the context of the logistics sector, it may also encourage efficiency improvements that lower costs and stimulate increased activity, thereby contributing to a larger rebound effect. However, if these regulations lead to significant cost savings, they may inadvertently encourage higher logistics activity (Banihashemi et al., 2019).

Although some of the explanatory variables are also used in energy consumption models, here they are used to explain the rebound effect and its decomposition—specifically, the extent to which energy efficiency improvements are offset by behavioral or structural responses. This focus distinguishes our analysis from standard energy consumption regressions.

Next, provinces with higher economic level typically have more advanced logistics infrastructure and technology, leading to greater operational efficiency (Lin and Cheng, 2019). However, higher economic level can also result in increased demand for logistics services (Munim and Schramm, 2018), and lead to higher energy consumption. The industrial structure influences the type and volume of goods transported, which in turn affects the logistics industry's energy consumption. Provinces with a more diverse and complex industrial structure may experience higher demand for specialized logistics services, increasing energy use (Wehner et al., 2022). On the other hand, provinces with a predominance of heavy industries may have higher baseline energy consumption (Vance et al., 2015). Lastly, higher residential consumption can drive increased demand for goods transportation, exacerbating the rebound effect (Liu and Chang, 2021). Provinces with rising consumption levels may see more pronounced increases in logistics, leading to higher energy use and emissions (Sheng et al., 2017).

Results for the regression are given in Table 6. In that table, we use the following notation to indicate the significance level for the regression coefficients: $***$ significant at 0.1%, $**$ significant at 1%, and $*$ significant at 5%.

Table 6: Estimates of Second Stage Regression

Variable	RE	EFF	$TECH$	$KACC$	$EACC$
Constant	0.68*	6.39**	-7.61*	-15.44**	17.35**
Government input	1.57***	0.81**	0.97***	2.07**	-2.28***
Environmental regulation	0.85***	2.80***	3.71***	6.92***	-6.98***
Economic level	0.55***	1.17**	1.09**	0.11	0.36
Industrial structure	0.24*	-0.03	-0.50*	-0.84**	1.19***
Resident consumption level	-0.03	-7.04***	9.24***	15.93***	-18.15***

Note: Regression estimates of the impact of government input, environmental regulation, economic level, industrial structure, and resident consumption on the rebound effect (RE) and its four decomposition components (EFF, TECH, KACC, EACC). Significance levels: ***, 0.1%, ** 1%, * 5%.

The regression results presented in Table 6 reveal the key factors driving the energy rebound effect (RE) in the Chinese logistics industry. All variables, except for resident consumption level, significantly influence the rebound effect. Government input and environmental regulation exhibit the largest positive coefficients, underscoring the vital role these policy-driven factors play in shaping energy efficiency. Their impact is particularly pronounced across the decomposition components, where both factors strongly enhance efficiency change, technological advancement, and capital accumulation while reducing energy accumulation. This suggests that policies aimed at increasing government investment and strengthening environmental regulations are crucial for fostering sustainable development in the logistics sector. The economic level also positively affects efficiency and technological change, though its impact is more moderate compared to government input and regulation. This indicates that wealthier regions tend to invest more in innovation and efficiency improvements, reflecting a regressive pattern where more economically advanced provinces benefit from better resource management and energy efficiency advancements. The industrial structure presents mixed effects: it negatively contributes to technological change and capital accumulation but positively affects energy accumulation. This suggests that shifts towards more energy-intensive sectors contribute to higher energy use, potentially reflecting increased demand for transportation and logistics services. These shifts may hinder innovation and investments in energy-efficient technologies, limiting improvements in productivity and sustainability within the sector. Lastly, resident consumption level shows a negative influence on efficiency change and energy accumulation but a positive effect on technological change and capital accumulation. This highlights the importance of managing residential consumption patterns and promoting sustainable practices to mitigate the negative impact on energy efficiency. Encouraging households to adopt energy-saving technologies and behaviors could help align consumption trends with broader energy efficiency goals in the logistics sector.

5 Conclusion

This study investigates the energy rebound effect in China's logistics industry across 31 provinces between 2011 and 2020. Such industry is counteracted by increased energy consumption and carbon emissions to support economic growth. Understanding how energy improvements are offset by the rebound effect is critical for designing effective energy and environmental policies. To do so, we suggest a new decomposition of the rebound effect into four dimensions: efficiency change, technological change, capital accumulation, and energy accumulation. Our decomposition is based on a production function framework and has therefore strong economic foundation. From an estimating point of view, we make use of a non-parametric estimation method that does not resort to assumptions nor require estimating parameters.

Our first-stage analysis reveals that the energy rebound effect in the Chinese logistics industry is largely positive, with an average of 0.76 across provinces. Provinces such as Gansu, Jiangxi, and Fujian exhibit the highest rebound effects, while a minority, including Hunan, Qinghai, Tianjin, and Inner Mongolia, show negative rebound effects. The decomposition highlights that technological change and capital accumulation are the primary drivers pushing up the rebound effect, while energy accumulation contributes negatively. Within China's logistics sector, our decomposition reveals three contrasting effects on the rebound. First, technological change (TECH) fuels rebound by reducing unit costs: when firms introduce efficiency-enhancing tools, such as automated sorters in major freight hubs or hybrid diesel-electric trucks, the lower price of logistics services spurs greater usage and, consequently, increased total energy consumption (the substitution effect). Second, capital accumulation (KACC) further drives rebound by backing advanced infrastructure—such as multi-story distribution centers in coastal regions and upgraded vehicle fleets—which lowers energy use per shipment but also enables a higher volume of goods moved, creating a pronounced scale effect. Finally, energy accumulation (EACC) works in the opposite direction: provinces that boost their energy input per worker through investments in on-site renewable generation at logistics parks or electrified cold-chain systems effectively swap out carbon-heavy fuels for cleaner electricity, thereby tempering the rebound rather than amplifying it.

To better understand the rebound effect results, we run a second-stage analysis. We select a set of key variables, including economic level, industrial structure, government input, environmental regulation, and resident consumption level, as independent variables for regressions with the rebound effect and its decomposition. level, as independent variables for regressions with the rebound effect and its decomposition. The second-stage regression analysis identifies government input and environmental regulation as the most significant drivers of the rebound effect in China's logistics industry, positively influencing efficiency change, technological advancement, and capital accumulation while negatively impacting energy accumulation. Economic level also plays a positive role in improving efficiency and technology, though its effects are more modest. In contrast, industrial structure shows a mixed impact, supporting energy accumulation but hindering technological change and capital accumulation. Resident consumption levels negatively affect efficiency and energy accumulation, highlighting the importance of managing consumption patterns to mitigate energy demand.

The policy implications of this research are significant, particularly the reconciliation of energy efficiency gains with the rebound effect. Policymakers must act to counteract measures that result in increased energy consumption brought about by cost reductions through efficiency. One of the key measures is the application of targeted energy pricing regimes that block the savings in energy from excessively driving higher consumption. Dynamic pricing schemes, carbon taxes, or cap-and-trade systems may be used to maintain economic incentives for energy conservation even as efficiency rises. In addition, clean energy infrastructure development will help ensure that any increase in energy demand through the rebound effect is met with renewable and not fossil-fuel-based energy sources, hence lowering environmental degradation.

Besides, technological innovation and the digitalization of logistics activities should be encouraged to decouple economic development from energy use. Regulations facilitating the application of intelligent logistics, freight routing optimization, and green transportation technology will most likely maximize energy savings and provide for industry growth. Increasing regulatory mechanisms, such as tighter fuel efficiency standards and environmental policy targeting logistics enterprises, are also set to minimize rebound effects by eliminating dependence on conventional energy sources.

Lastly, concerning rebound effects differences between provinces, policy interventions need to be tailored in response to regional industrial and economic frameworks. More developed provinces should face stricter rules and targeted incentives for energy-efficient technologies, while less developed areas can enjoy capacity-building programs for logistics efficiency improvement without overexpansion of energy. By integrating these strategies, policymakers can better balance the economic growth and energy efficiency trade-offs in a way that sustainability goals are met without being undermined by perverse rebounds in energy consumption.

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Appendix

Table 7: Literature review – logistics industry in China

Authors	Output	Inputs	Energy intensity
Wang and Xin, 2020	added value, CO_2 emissions	people employed, fixed assets investment, energy consumed	N/A
Liang et al., 2022b	freight volume, transported cargo product, GDP, CO_2 emissions	transportation lines, capital stock, employees	N/A
Yu et al., 2023	added value, freight turnover, passenger turnover, CO_2 emissions	employees, total investment in fixed assets, total energy consumption	N/A
Chen et al., 2024	added value, freight turnover, carbon dioxide emissions	employees, capital stock, transport route mileage, operating vehicles, postal network points, consumption of energy	N/A
Ding and Liu, 2024	freight transport, goods turnover, added value, CO_2 emissions	employees, fixed assets, trucks, network mileage, energy consumption	energy consumption to output value
Yao et al., 2024	GDP, freight transport, turnover volume, carbon dioxide emissions	employees, transportation lines, fixed-asset investment, energy consumption	N/A

Table 8: Rebound effect per period

Province	2012 -2011	2013 -2012	2014 -2013	2015 -2014	2016 -2015	2017 -2016	2018 -2017	2019 -2018	2020 -2019	Av.
Anhui	-0.21	25.63	1054.75	2.92	0.36	-2.25	1.04	1.00	5.33	120.95
Beijing	2.79	0.90	4.56	-24.87	4.05	2.61	0.99	1.14	-0.96	-0.98
Chongqing	-0.32	-22.89	0.67	-0.84	2.61	1.86	-0.12	1.43	-0.48	-2.01
Fujian	0.30	-5.52	4.30	1.33	5.54	1.65	0.77	1.51	0.19	1.12
Gansu	3.17	0.53	0.73	-1.31	-7.95	0.75	0.65	2.41	1.25	0.03
Guangdong	0.71	-1.86	7.03	4.30	-4.59	1.01	1.10	1.33	-0.34	0.97
Guangxi	0.15	-0.19	-0.55	2.78	4.38	4.98	0.81	0.75	0.27	1.49
Guizhou	-5.19	-0.63	90.33	14.84	-1.54	0.39	0.83	0.76	-5.91	10.43
Hainan	0.99	-1.06	0.87	5.17	-0.25	1.63	2.33	1.37	5.05	1.79
Hebei	-2.01	-1.55	-0.39	0.68	-0.09	1.76	1.40	-0.77	0.04	-0.10
Heilongjiang	-0.27	0.87	3.15	3.52	1.21	-6.93	-0.39	1.01	-1.03	0.13
Henan	0.88	-1.74	1.13	14.25	0.83	1.33	5.62	0.73	4.38	3.05
Hubei	0.79	-1.08	0.79	2.15	-0.13	1.22	1.17	1.88	2.92	1.08
Hunan	1.62	-0.62	-2.63	-1.27	17.27	1.51	0.12	-0.70	1.25	1.84
Inner Mongolia	6.19	-0.48	6.61	0.72	-0.23	-0.01	1.22	0.15	-0.79	1.49
Jiangsu	3.53	264.25	0.04	-7.00	3.29	2.57	0.25	1.23	3.82	30.22
Jiangxi	1.33	3.60	3.57	-0.41	1.81	1.97	-0.89	1.83	0.27	1.45
Jilin	-2.96	0.16	5.17	-0.51	2.78	0.70	0.66	1.64	0.79	0.94
Liaoning	1.33	-0.63	-21.74	1.30	0.82	0.53	-1.08	0.99	0.26	-2.02
Ningxia	-0.70	19.54	-0.41	-1.41	-1.49	0.52	-5.42	1.92	1.14	1.52
Qinghai	-0.13	17.23	6.88	-4.29	-0.56	-0.01	-0.87	0.01	0.84	2.12
Shaanxi	1.55	-1.16	3.22	1.40	2.00	7.69	1.75	0.98	0.09	1.95
Shandong	1.75	-0.53	0.71	3.04	1.56	2.52	0.85	58.86	-0.51	7.58
Shanghai	4.22	-5.31	0.58	2.32	-8.45	-23.76	1.39	1.13	-0.77	-3.18
Shanxi	0.52	-0.88	1.39	2.31	8.92	2.08	2.15	0.79	-0.24	1.89
Sichuan	0.44	-1.29	-13.27	1.37	-1.24	5.17	0.83	2.25	-2.26	-0.89
Tianjin	-10.02	0.17	-0.01	-0.12	-0.45	1.91	1.43	1.39	0.48	-0.58
Tibet	0.52	0.06	-5.19	-0.67	1.05	-7.58	3.78	-3.22	-5.30	-1.84
Xinjiang	1.21	13.55	2.09	-2.09	15.33	1.35	0.74	0.99	2.48	3.96
Yunnan	1.34	-0.90	-0.54	0.68	4.68	0.20	1.18	1.34	-0.16	0.87
Zhejiang	-7.76	3.05	0.86	16.54	1.28	1.74	0.60	0.47	3.38	2.24
Av.	0.19	9.72	37.25	1.19	1.70	0.29	0.80	2.79	0.50	6.05