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An autoregressive spatial stochastic frontier analysis for quantifying the sales efficiency of the electric vehicle market: An application to 88 pilot cities in China

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A R T I C L E I N F O

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A B S T R A C T

This paper proposes the use of an autoregressive spatial stochastic frontier model to measure the sales efficiency of the electric vehicle (EV) market in 88 Chinese cities for the period 2016 to 2023. In contrast to previous research on this topic, the adoption of a stochastic frontier model allows for computing the maximum level of EV sales (i.e., frontier) that each city could have potentially achieved in the timeframe under assessment given a certain set of inputs (e.g., central and local purchase subsidies, subsidies for the construction/operation of electric vehicle chargers, average petrol prices, purchase restrictions on conventional vehicles, among others). Further, the spatial-based structure of the model proposed enables the evaluation of the impact of similar policy interventions implemented in neighbouring cities on EV sales frontier estimated within the city. The empirical evidence suggests that as the provision of EV charging stations around and within the city increases, so does the maximum number of sellable electric cars. A further interesting finding is that the frontier for EV sales is positively influenced by the electric cars purchased in the previous month in neighbouring areas, revealing the presence of a strong spatial dependency. Finally, this study conducts a simulation exercise wherein three hypothetical scenarios are explored: (1) the implementation of a ten percent tax on petrol, (2) a ten percent increase in the number of public chargers available, and (3) the introduction of policies to improve the air quality of all 88 cities. The results from the simulation analysis suggests that improving the number of public charging stations by 10 percent would have resulted in the sales of nearly 41,000 EVs more across the 88 cities over eight years.

1. Introduction

The threat of global warming on human health has led international and national governments to implement a series of

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environmental intervention strategies in the attempt to effectively combat the climate change crisis. Given that the transportation sector continues to be the third world's largest polluter of carbon emissions, many of these strategies focus on speeding up the transition to electromobility (Zhang et al., 2013; IEA, 2015; Avci et al., 2015). In 2022, the International Energy Agency (IEA) quantified that worldwide, transportation related emissions made up approximately one quarter of total CO_2 produced, 75 percent of which were generated from road travel trips whilst the remaining 25 percent were released by shipping and aviation sources (IEA, 2022). Because of the level of emissions derived from road transport and the heavy reliance of the sector on fossil fuels, the mass adoption of electric vehicles (EVs) represents one of the quickest and most viable options to achieve net-zero targets (Nanaki and Koroneos, 2016; Yu and Stuart, 2017; Jang and Choi, 2021).

Currently, there exist multiple types of EVs on the market, from plug-in hybrid electric vehicles (PHEVs) to battery electric vehicles (BEVs). PHEVs pair a traditional internal-combustion engine (ICE) with a battery-powered electric motor, with the former typically being engaged when the battery is nearly depleted or during high-speed manoeuvring. The redundant nature of the operating system that the ICE offers makes PHEVs particularly attractive amongst consumers who hold concerns with respect to the limited driving range capacity of BEVs (Mulholland et al., 2018). Although PHEVs emit tailpipe pollution whilst using the ICE, the presence of an electric motor allows for travelling moderate distances using only clean energy (i.e., electricity), resulting in lower emissions relative to vehicles powered solely by petrol or diesel engines (Darabi and Ferdowsi, 2012). BEVs in contrast, depend fully on rechargeable battery packs which are charged either at private or public charging stations, as well as from the installation of solar panels on the vehicles themselves (Masuda et al., 2017; Girard et al., 2019; Araújo et al., 2019; Ghasri et al., 2021). Further, the absence of a piston engine makes driving BEVs smoother and tends to generate less noise compared to conventional fuelled vehicles (Sheng et al., 2022).

Over the past decade, the size of the EV market has rapidly expanded with the new EV registrations reaching 14 million units in 2023, increasing by 14 percent compared to 2022 (IEA (2023)). Despite global conflicts and microchip shortages, China remains at the forefront of the transition towards greener mobility accounting for approximately 60 percent of global EV sales (8.1 million electric cars were sold in 2023). Of the newly registered vehicles, nearly 77 percent were reported to be BEVs whilst the reaming 23 percent were classified as PHEVs. Further, China's electric vehicle fleet currently exceeds 20 million cars, nearly double the size of Europe's EV stock. The impressive development of the Chinese EV market is largely attributable to the great variety of economic policies set out by the Chinese Government (CG) over the years. In 2009, for example, the CG announces the *Ten Cities and Thousand Vehicles* demonstration project which aims at reaching the sale of at least 1,000 EVs in each of the ten targeted cities via the provision of a one-off purchase subsidy (OECD, 2009). After three years, the second demonstration project is launched bringing the overall number of pilot cities to 88. More recently, China introduced the *14th Five-Year Plan (FYP) 2021–2025*, which comprises a wide range of initiatives specifically design to consolidate the growth of EVs into the automobile sector. Such initiatives include, but not limited to, subsidies to reduce electric car up-front costs, investments to strengthen the public charging network, the issuance of tax breaks and travel restrictions placed on the sale and use of ICE vehicles (IEA, 2021).

A large body of the transportation literature has examined the impact of various government intervention policies on the demand for EVs, with studies tending to be classified into two broad groups depending on the source of data used to carry out the empirical analysis (Kong and Hardman, 2019; Liao et al., 2017; Casta et al., 2021; Chakraborty et al., 2022; Dua et al., 2024). The first group of studies assesses disaggregate data on consumers' preference behaviour towards EVs usually extracted from discrete choice experiments (DCEs) embedded with web-based questionnaires (Hidrue et al., 2011; Hess et al., 2012; Hackbarth and Madlener, 2013; Chorus et al., 2013; Hoen and Koetse, 2014; Cherchi, 2017; Jenn et al., 2020). For example, Horne et al. (2005) analysed data obtained from a DCE completed by 1,150 Canadian residences and concluded that respondents would be inclined to move away from ICE cars if the national government allowed fuel-efficient vehicles to access express lanes. This finding is in contrast with the results obtained by Qian and Soopramanien (2011), who found that neither dedicated lane access nor free parking spots for five years would influence respondents' preferences towards the acquisition of an EV. Potoglou and Kanaroglou (2007) suggested that the sales of either hybrid or alternative fuelled vehicles would be increased by lowering sales tax (see, also, Adler et al., 2003). Mau et al. (2008) reported that government subsidies for new technology vehicle purchases would be the most effective solution to stimulate EV roll out, followed by extended warranties (see, also, Glerum et al., 2014). Caulfield et al. (2010) pointed out that high vehicle registration taxes would have the least negative effect on those respondents who expressed the intention to buy a new hybrid electric vehicle, whilst Gong et al. (2020) indicated that government rebates on energy bills and parking costs would strengthen the EV diffusion in Australia. Pellegrini and Rose (2023) predicted that the potential deployment of massive subsidies by the Australian government to reduce purchase prices of BEVs and PHEVs will result in more electric cars on roads in the future vis-à-vis faster home charging infrastructure. Similarly, Wenjian and T. Donna (2023) concluded from a DCE administrated in Virginia that the provision of monetary incentives is the most effective policy intervention to ramp up the sales of EVs. From an infrastructure standpoint, Pellegrini et al. (2023) asserted that introducing a quarterly electricity bill discount subsidy is likely to encourage apartment owners to invest in the installation of private home chargers. This, in turn, could boost the adoption of fuel-efficient vehicles given that prospective customers would have an alternative charging option to public charging outlets.

The second group of studies, on the other hand, apply aggregate level analysis to historical vehicle sales data collected either at the international or national level (Ajanovic and Hass, 2016; Coffman, Bernstein and Wee, 2017). For example, Sierzchula et al. (2014) examined the automobile markets from across 30 different countries and computed an increase of the EV market share (calculated as a percentage of annual car sales) of 0.06 percent for every additional $1,000USD in financial support (see, also, Duan, Gutierrez and Wang, 2014). Sheldon and Dua (2020) investigated the relationship between EV sales and high-occupancy vehicle (HOV) lanes and found that granting electric cars access to HOV increased the EV sales in California by up to 25 percent (see, also, Jenn et al. 2018). Wang et al. (2017) fitted multiple linear regression models on EV sales data collected between 2013 and 2014 from 41 Chinese cities, which were selected to be part of a demonstration project (i.e., pilot cities). The authors identified the number of chargers per million square kilometres as the most important predictor for the sales of EVs. Ma et al. (2017) made use of a multivariate cointegration model, suggesting that the introduction of restrictions on conventional vehicle purchases positively influenced the promotion of EVs in China (see, for similar findings, Chi et al., 2021; Liu et al., 2021; Ma and Fan, 2020; Yao et al., 2022; Zheng et al., 2022). Qiu et al. (2019) conducted a panel data analysis by using monthly data on EV sales from 88 Chinese pilot cities for the years 2014 and 2015, pointing out that both charging discount and infrastructure construction subsidy were found to be essential for the market breakthrough of EVs (Ou et al., 2020), whereas the provision of purchase incentives had no effect on EV sales. Mukherijee and Ryan (2020) found that the distance to the nearest charging point and access to car dealers are pivotal predictors for the EV uptake amongst early adopters in Ireland. Sheng et al. (2022) concluded there exists a charging infrastructure spatial effect on the decision to purchase EVs in New Zealand. In similar vein, He et al. (2022) implemented a spatial economic model to explore potential neighbourhood effects on EV uptake and established that the increasing adoption of EV was in part due to the number of charging stations available in the neighbouring cities. Sinton et al. (2024) analysed ZIP code level data from US states of California, Colorado, New York and Washington, revealing that densely populated areas were associated with low take-up rates of EV, whilst high-income zones exhibited greater uptake of fuel-efficient vehicles. Lastly, Pan, Uddin and Lim (2024) concluded that public chargers accessible within a 10 mile-radius encouraged early prospective customers to move away from ICE cars.

In all the aforementioned studies using historical ownership data, the underlying assumption is that the EV sector operates in a technically efficient manner. This entails that the observed EV sales are implicitly assumed to represent the maximum possible number of vehicles that could be sold, given the existing inputs (e.g., infrastructure, legislations/regulations, incentives, technology, etc.). However, factors such as the premature removal of monetary incentives or the insufficient expansion of the public charging infrastructure network may have hindered the performance of the EV sector, thereby inducing productive inefficiency (Diaź-Hernàndez et al., 2008). If such inefficiency persists or even worsens overtime, it is likely to further widen the gap between observed and maximum achievable EV sales. Therefore, disregarding the potential existence of technically inefficiency might affect the reliability of the model estimates, resulting in erroneous predictions as to how the EV market under assessment will evolve.

Against this background, this paper proposes the use of an autoregressive spatial stochastic frontier (SF) to analyse the monthly EV sales performance of 88 demonstration Chinese cities (see, for further details, Yao et al., 2022) during the time-period from January 2016 to December 2023. The proposed spatial–temporal SF approach allows for quantifying the maximum level of sales (i.e., frontier) that each demonstration city could have possibly achieved within the specified timeframe, given a set of inputs such as number of public chargers, conventional vehicle purchase restrictions, national and local subsidies, and average petrol prices, among others. Whilst the sales of EVs are observed at the city level, so is the list of inputs, the possible achievable frontier of EV sales is latent. As such, by computing the difference between the latent frontier and the observed EV sales, we are able to determine as to whether each pilot city has succeeded in maximizing their output (and hence being technically efficient), given the bundle of available inputs. Further, the implemented spatial structure enables the evaluation of the impact of spill-over effects on the unobserved frontier of EV sales that may arise from similar policy reforms introduced in neighbouring areas (see, for example, Sheng et al., 2022).

To date, SF methods have been extensively used to carry out economic efficiency analysis in transport (see, for example, Yan et al., 2009; Sohn and Jung, 2009; Wanke et al., 2011; Sun et al., 2015; Filippini et al., 2015; Balliauw et al., 2018; Yang et al., 2020; Ripoll-Zarraga and Huderek-Glapska, 2021). One of the early applications of SF techniques traced back to Cullinane et al. (2006), who investigated the effect of administrative and ownership structures on productive efficiency of major container ports in Asia (see, also, Ha et al., 2013; Panayides et al., 2011; Scotti et al., 2012; Chang and Tovar, 2014; Coto-Millan et al., 2016). Hidalgo-Gallego and Mateo-Mantecon (2019) adopted a SF model for examining the interplay between airline concentration and airport efficiency using data from a sample of 41 Spanish airports. Pinjari et al. (2016) exploited the features of the SF to measure the unobserved time-use allocation budget. Similarly, Pellegrini et al. (2021) made use of a cross-sectional SF model to quantify the latent frontier monetary budget within a context of leisure trips in Switzerland. To the best of our knowledge, the current work represents the first application of a SF analysis to evaluate the economic efficiency of the EV sector.

The reminder of the paper is structured as follows. The next section illustrates the features of the employed SF approach, whereas Section 3 presents the descriptive statistics of the output (i.e., EV sales) and input variables used in this study. Section 4 describes the empirical findings, followed by the penultimate section wherein the results of a simulation exercise are outlined. Section 6 provide concluding remarks.

2. Methodology

In this section, we describe the autoregressive spatial stochastic frontier (henceforth, AS-SF) model used to investigate EV sales productivity. Since the seminal work of Aigner, Lovell and Schmidt (1977), SF analysis has been advanced in several directions. For example, Battese and Coelli (1995) formulated a SF structure for panel data in which technical efficiency can be specified as a function of explanatory variables (see, also, Stevenson, 1991; Huang and Liu, 1994). Schmidt et al. (2009) went on to integrate latent spatial dependency into the backbone of the SF to account for potential geographical variations in outputs. This methodological advancement was rooted in the research question posed by Baptista (2000), who asserted that geographical proximity fosters collaboration between firms, thereby boosting the underlying productivity. More recently, Tsukamoto (2019) extended the functional form of Battese and Coelli to accommodate spatial effects, whilst Galli (2023) introduced further flexibility by allowing the efficiency to be expressed as a combination of spatial and non-spatial variables. The proposed AS-SF grounds upon the specification formalized in Tsukamoto (2019), where spatial dependencies are captured solely within the frontier.

Consider the Cobb-Douglas stochastic production frontier function for panel data on EV sales collected at the city level:

$$\ln(Y_{it}) = \ln(Y_{it-1})\rho + \lambda W\ln(Y_{it-1}) + \ln(x_{it})\beta + \ln(x_{it-1})r + \delta W\ln(x_{it}) + \theta W\ln(x_{it-1}) + V_{it} - U_{it}. \tag{1}$$

In the above equation, Y_{it} corresponds to the number of electric cars sold by the pilot city i ($i = 1,\cdots,88$) in the t^{th} month ($t = 2,\cdots,T$), and x_{it} is a ($1 \times l$) vector of values of input variables describing the pilot city i in the t^{th} month. The timeframe for analysis spans 95 months beginning from February 2016 ($t = 2$) to December 2023 ($T = 95$) due to the autoregressive nature of the model. Rather than imputing a value of zero for the sales of electric and conventional automobiles registered in *t-1* for each pilot city, we resorted to the first data point available in the time series, namely January 2016. In doing so, we assure that the underlying ergodicity property of the timeseries is retained throughout the entire estimation of the log-likelihood function. A further aspect that we explore in this study relates to potential spill-over effects that may originate from similar political initiatives adopted in neighbouring cities to promote the diffusion of EVs. Specifically, we employed a rock contiguity algorithm to compute the weights (w_{ii} with $i = 1,\cdots,88$) of the distance matrix W, in which its diagonal elements are equal to zero whilst its off-diagonal elements are assumed to take the value of one if two geographic objects (i.e., pilot cities) are *near* each other, or 0 otherwise (see, for example, Cohen, 2010; Arbués Baños and Mayor, 2015; Bhat et al., 2016; Yang et al., 2023). β is a $(l \times 1)$ vector of unknown parameters to be estimated, whilst ρ, λ, δ and θ are scalar parameters to be estimated, with $-1 \le \rho \le 1$, and $0 \le \lambda \le 1$. V_{it} are independently and identically normally distributed (IID) error terms, $N(0,\sigma_V^2)$, and U_{it} are non-negative random variables related to the technical inefficiency of production, which are assumed to be independently distributed of the V_{it} for all $t = 1,\cdots,T$ and $i = 1,\cdots,I$. U_{it} can be further parametrized as $U_{it} = f_{it}\alpha + \Lambda_{it}$ such that U_{it} results from the truncation (at zero) of the normal independent distribution with mean, $f_{it}\alpha$ and variance, $\sigma^2.f_{it}$ is a ($1 \times q$) vector of explanatory variables associated with the technical inefficiency of production over time whilst α is a ($q \times 1$) vector of unknown parameters to be estimated. The underlying assumption here is that the random variable Λ_{it} $N(0,\sigma^2)$, is specified such that the point of truncation is defined as $\Lambda_{it} \ge -f_{it}\alpha$. It should be noted that the SF formulated in Equation (1) collapses to that developed in Aigner et al. (1977) if the explanatory variables embed within the technical inefficiency component of the model,f_{it}, are normalized to zero. Let Z_{it} be defined as follows: $Z_{it} = \ln(Y_{it-1})\rho + \lambda W\ln(Y_{it-1}) + \ln(x_{it})\beta + \ln(x_{it-1})r + \delta W\ln(x_{it}) + \theta W\ln(x_{it-1})$. Next, the density function for the Y_{it} as expressed in Equation (1) is given by

$$f_{Y_{it}}(y_{it}) = \frac{\exp\left[-\frac{1}{2}\frac{\left(y_{it}-Z_{it}+f_{it}\alpha\right)^2}{\sigma_V^2+\sigma^2}\right]}{\sqrt{2\pi\left(\sigma_v^2+\sigma^2\right)^{1/2}\left[\Phi(d_{it})/\Phi(d_{it}^*)\right]}}, \tag{2}$$

where $d_{it} = \frac{f_{it}\alpha}{\sigma}$, $d_{it}^* = \frac{\mu_{it}}{\sigma}$, $\mu_{it} = \frac{\left[\sigma_V^2 f_{it}\alpha - \sigma^2\left(y_{it}-Z_{it}\right)\right]}{\sigma_V^2+\sigma^2}$ and $\Phi(\bullet)$ refers to the distribution function for the standard normal random variable.

Then, the logarithm of the likelihood function for the sample observations $y = (y'_{11}, y'_{12}, \cdots, y'_{IT})'$ can be written as

$$\begin{aligned} L = (\phi;y) = &-\frac{1}{2}\sum\nolimits_{i=1}^{I} t_i\left[\ln(2\pi) + \ln\left(\sigma_V^2+\sigma^2\right)\right] \\ &-\frac{1}{2}\sum\nolimits_{i=1}^{I}\sum\nolimits_{t=1}^{T}\left[\frac{\left(y_{it}-Z_{it}+f_{it}\alpha\right)^2}{\sigma_V^2+\sigma^2}\right] \\ &-\frac{1}{2}\sum\nolimits_{i=1}^{I}\sum\nolimits_{t=1}^{T}\left[\ln\left(\Phi(d_{it}) - \Phi(d_{it}^*)\right)\right], \end{aligned} \tag{3}$$

where $\phi = (\beta,\rho,\alpha,\lambda,r,\delta,\theta,\sigma_S^2,\gamma)$, $d_{it} = \frac{f_{it}\alpha}{\sqrt{\gamma\sigma_S^2}}$, $d_{it}^* = \frac{\mu_{it}}{\sqrt{\gamma(1-\gamma)\sigma_S^2}}$, $\mu_{it} = (1-\gamma)f_{it}\alpha - \gamma(y_{it} - Z_{it})$, $\sigma = \sqrt{\gamma(1-\gamma)\sigma_S^2}$.The log-likelihood function in Equation (3) can be re-specified in terms of the variance parameters $\sigma_S^2 = \sigma_V^2 + \sigma^2$ and $\gamma = \frac{\sigma^2}{\sigma_s^2}$ as follows:

$$\begin{aligned} L = (\phi;y) = &-\frac{1}{2}\sum\nolimits_{i=1}^{I} t_i\left[\ln 2\pi + \ln\left(\sigma_S^2\right)\right] \\ &-\frac{1}{2}\sum\nolimits_{i=1}^{I}\sum\nolimits_{t=1}^{T}\left[\frac{\left(y_{it}-Z_{it}+f_{it}\alpha\right)^2}{\sigma_S^2}\right] \\ &-\frac{1}{2}\sum\nolimits_{i=1}^{I}\sum\nolimits_{t=1}^{T}\left[\ln\left(\Phi(d_{it}) - \Phi(d_{it}^*)\right)\right] \end{aligned} \tag{4}$$

The method of maximum likelihood is used to simultaneously estimate the vector of unknown parameter ϕ, wherein γ represents the variance of the inefficiency effects. The technical inefficiency of production for the i^{th} pilot city at the t^{th} month is therefore computed as

$$TE_{it} = \exp(-U_{it}) = exp(-f_{it}\alpha - \Lambda_{it}). \tag{5}$$

The reader will note that the prediction of the technical efficiencies of the EV market at the city level is obtained from its conditional expectations conditioned on the model assumptions.

3. Data

This section outlines the output and input variables used in the estimation of the stochastic frontier model that we introduce in the previous section. We first illustrate the output variable, EV sales, followed by an explanation of the set of inputs incorporated into the stochastic frontier and inefficiency components.

3.1. Output variable

The core variable of this study refers to the monthly sales of BEVs and PHEVs (*Salev*) collected at the city level between January 2016 and December 2023. Table 1 displays the aggregate annual sales of EVs (*Salev*) and conventional vehicles (*Salcv*) for the timeframe 2016–2023, respectively. From the table, it emerges that the sales volume of EVs remarkably raised from 2016 to 2023 reaching 1,134,017 units sold in 2023, albeit after exhibiting a significant drop in 2022 because of the Covid-19 pandemic. On the other hand, the growth of PHEV market has been notably unstable between 2016 and 2021, with only 953 automobiles sold in 2019, down from 12,052 the previous year. In the period 2022–2023, however, the sales of PHEVs reached 6,092,092 units, half of which were sold in 2023 alone. The annual average market of the EV sector amounts to 11.20 percent of all automobiles sold across the 88 pilot cities.

3.2. Input variables

The SF specification proposed allows for expressing both the latent frontier and the inefficiency as a function of socio-economic and environmental characteristics of the demonstration cities recorded throughout the time-period 2016–2023. First to be described is the list of variables of the stochastic frontier after which the inputs embedded within the inefficiency are presented.

3.2.1. Inputs of the stochastic frontier

A wide range of variables is employed to examine the stochastic frontier of the EV sales. The first two variables that we present refer to the restrictions introduced to slow down the proliferation of conventional passenger vehicles, namely *Purr* and *Drir*. *Purr* represents the restrictive measures imposed to limit the purchase of ICE vehicles, whereas *Drir* relates to driving restrictions applied to ICE vehicles on some roads of the pilot cities. In addition to *Purr* and *Drir*, we also include in the stochastic frontier the sales of conventional vehicle (*Salcv*), which captures the effect of conventional vehicle purchases on EV uptake. The next two inputs are summer (*Sumr*) and temperature (*Temp)*: *Sumr* is a dummy variable that takes the value of one if months within the time series fall in June, July, and August, and zero otherwise; *Temp* takes the value of one if the average monthly temperature is reported to be below zero, and zero otherwise. Several studies so far have explored the relationship between temperatures and EV ownership. For example, Zou et al. (2016), Demircali et al. (2018) and Hao et al. (2020) state that extreme temperatures decrease both the battery capacity and the driving range, whilst also augmenting the charging frequency. Koncar and Bayram, 2021 find that cold temperatures on the other hand imper battery efficiency and internal resistance. Further, Vergis and Chen (2015), Yang et al. (2023) and Li et al. (2023) suggest there exists a negative correlation between EV market shares and low temperatures. To measure the impact of air quality on EV adoption, we create a dummy variable, *Airq,* which takes the value of one if the average PM2 level recorded is less than 35 μg/m3, and zero otherwise. Zhao et al. (2024) asserted that, despite the vast literature on EVs, little is still known as to how consumers' preferences for EVs changes due to improvement in the air quality. The authors posit that the intention of consumers to buy EVs becomes more evident as the air quality deteriorates. The influence of population size on the EV uptake is measured via a dummy variable, *Pop_Den*, which takes the value of one if the number of people per square meter is lower than 492,740, and zero otherwise. For example, Chen et al. (2013) and Xiong and Wang (2020) conclude that the likelihood of purchasing EVs is likely to increase in densely populated cities due to traffic congestions and limited parking availability. Three continuous variables also belong to this list of inputs of the stochastic frontier: the average monthly petrol price (*AvgPetrP*), and average annual GDP per capita (CHY) reported at the city level (see, Diamond, 2009; Wang, Tang, and Pan, 2019), the number of public chargers at the province level (*Chan*) (see, Sheng et al. 2022; He et al., 2022). Given that the time series spans the Covid-19 pandemic period, we create two dummy variables: *Movr* takes the value of one if the city implemented movement restriction policies to contain the transmission of the Covid-19 virus, and zero otherwise; *Covid-19* takes the value of one between January 2020 and December 2022, and zero otherwise.

3.2.2. Inputs of the efficiency

The battery of inputs that we adopt for assessing EV sales efficiency comprises four variables. Of these variables, three represent the financial support deployed by CG to promote EV purchase and usage: central (government) financial purchase subsidies (*Cenfs*), local

Table 1
Vehicle Sales in 88 prefecture-level cities from 2016 to 2023.

Fuel type	Timeframe of the current study							
	2016	2017	2018	2019	2020	2021	2022	2023
BEVs	169,995	378,961	576,032	538,655	636,526	1,593,799	757,959	1,134,017
PHEVs	2,194	2098	12,052	953	138,032	342,298	2,722,479	3,369,613
ICEVs	14,759,789	14,855,033	13,994,350	13,355,349	12,461,062	13,303,363	9,671,874	9,131,145

(government) financial purchase subsidies (*Locfs*), and local (government) financial charger subsidies (*Chas*) variables. Specifically, the *Cenfs* were designed such that the government monetary contribution gradually diminished over time, thereby accelerating the transition of the EV industry from one that is policy-driven to one that is market-driven. Table 2 outlines the scale-back purchase subsidy plan implemented under the *Cenfs* program in each of the 88 pilot cities under investigation between 2016 and 2022. As shown in the table, the amount of subsidy that consumers could access was primarily tied to the driving range capacity of the EV purchased. In 2016, for example, the purchase of a BEV with a driving range between 100 and 150 km (km) benefited from a discount of 25,000 CHY ($3,452 USD), whereas one with a driving range of more than 250 km was subject to a discount of 55,000 CHY ($7,594 USD).

However, the maximum purchase rebate available in 2021 stood at only 18,000 CHY ($2,485 USD) for an EV with a driving range of at least 400 km. Likewise, the financial support for the acquisition of PHEVs progressively reduced from 30,000 CHY ($4,142 USD) in 2016 to 6,800 CHY ($938 USD) in 2021. With respect to the *Locfs*, the CG announced in 2017 that the financial stimuli provided by local authorities could not exceed 50 percent of the value of *Cenfs*. The fourth and last variable indicates whether the CG provided income support to households during the Covid-19 pandemic or not.

3.3. Data collection and descriptive statistics

The output (*Salev*) and input variables are collected on a monthly basis for each pilot city between January 2016 and December 2023. The corresponding descriptive statistics across the 88 cities over the eight years for which data are captured are given in Table 3. Both sales of EVs (*Salev*) and conventional vehicles (*Salcv*) are obtained from the Traffic Management Bureau office of the pilot city under. From Table 3, there exists a divergence in the monthly sale volumes between electric and conventional vehicles, with the maximum number of fuel-efficient cars sold being 52,205 against 106,410 traditional automobiles in a given month. Information on central government financial purchase subsidies (*Cenfs*) was obtained from official policy documents available on websites of the central government, Ministry of Science and Technology, Ministry of Finance, and Ministry of Industry and Information Technology, respectively. To reflect the scale-back nature of *Cenfs*, we calculated the proportion of purchase incentives with respect to 2016, with the latter being the base year wherein the largest monetary contribution was deployed. The local government financial purchase subsidies (*Locfs*) and charger subsidies (*Chas*) were obtained from different sources such as the People's Government of each pilot city, the Bureau of Finance, the local Bureau of Industry and Information Technology, and the Bureau of Development and Reform. Given the inconsistency in the data collection format across the 88 pilot cities, we created two dummy variables representing whether the city provided subsidies for the purchase of EVs (*Locfs*), and the second representing whether public charger construction/operation (*Chas*) subsidies were available. The mean values for *Locfs* and *Chas* are 0.29 and 0.71, respectively, suggesting that subsidies for the installation of public chargers were on average available for a longer period of time relative to that for the acquisition of fuel-efficient automobiles.

Documents from local transportation administrations were utilized for the construction of the dummy variables representing purchase (*Purr)* and driving (*Drir*) restrictions imposed on conventional vehicles. The corresponding means for these variables are found to be similar in magnitude and therefore we can conclude that such restrictions were on average in place for an equal amount of time. Data on temperature, air quality, monthly petrol price, annual GDP per capita at the city level, and all Covid-19 related variables were extracted from different sources. In the case of city temperatures, we resorted to the China Weather Network (https://www.weather.com.cn), whereas the China Air Quality Online Monitoring and Analysis Platform (https://www.aqistudy.cn) and the Oriental Fortune (https://www.eastmoney.com) were consulted for the concentration level of PM2 in the air and the monthly average petrol prices, respectively. Data on population density per meter square and average annual GDP per capita were, on the other hand, obtained from the 2016–2023 China Urban Statistical Yearbook. The average petrol price over the eight-year period stands at CHY 6.711 per litre with a standard deviation of 1.13 CHY per litre. In terms of population distribution, it appears that most of the demonstration cities have a population greater than 492,749 km^2. To control for the impact that the ongoing Covid-19 pandemic has on consumer purchase behaviour, *Movr,* and *Govsp* were created based upon information available on the Oxford Covid-19 Government Response Tracker website (https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker). We assembled data on the number of public chargers (*Chan*) by examining the China Electric Vehicle Charging Infrastructure Promotion Alliance website (https://www.evcipa.org.cn). Lastly, *Covid-19*, entered into the model as a proxy for the Covid-19 pandemic.

Table 2
Central government's financial subsidy in 2016–2022.

Time	National subsidy for EV and PHEV
2016	**BEV:** $100 \leq R < 150$:2.5;$150 \leq R < 250$:4.5; $R \geq 250$:5.5. **PHEV:** $R \geq 50$:3.
2017	**BEV:** $100 \leq R < 150$:2;$150 \leq R < 250$:3.6; $R \geq 250$:4.4. **PHEV:** $R \geq 50$:2.4.
2018	**BEV:** $150 \leq R < 200$:1.5;$200 \leq R < 250$:2.4;$250 \leq R < 300$:3.4;$300 \leq R < 400$:4.5; $R \geq 400$:5. **PHEV:** $R \geq 50$:2.2.
2019	**BEV:** $250 \leq R < 400$:1.8; $R \geq 400$:2.5. **PHEV:** $R \geq 50$:1.
2020	**BEV:** $300 \leq R < 400$:1.62; $R \geq 400$:2.25. **PHEV:** $R \geq 50$:0.85.
2021	**BEV:** $300 \leq R < 400$:1.3; $R \geq 400$:1.8. **PHEV:** $R \geq 50$:0.68.
2022	**BEV**: $300 \leq R < 400$:0.91;$\mathbf{R} \geq 400$:1.26. **PHEV**: $R \geq 50$:0.48.

* R: Battery electric range (km); BEV: Battery electric vehicle; PHEV: plug-in hybrid electric vehicle. The unit of subsidies is CNY 10,000 (equal to about $1,500). The financial support plan ended in 2022.

Table 3
Descriptive statistics.

Variables	Variables Definition	Mean	S.D.	Max.	Min.
	Output variable				
Salev	Sales of PHEVs and BEVs	732.461	2,049.332	52,205	0
	List of input variables				
Salcv	Sales of ICEVs	11,498.623	11,578.193	106,410	0
Cenfs	Central government financial purchase subsidies (2016 is base)	0.450	0.324	1	0
Locfs	1 if local government provide financial purchase subsidies; 0 otherwise	0.292	0.455	1	0
Chas	1 if local government provides subsidies for construction/operation of public chargers; 0 otherwise	0.710	0.452	1	0
Sumr	1 if the season is summer (June, July and August); 0 otherwise	0.253	0.435	1	0
Temp	1 if the temperature is below 0; 0 otherwise	0.092	0.288	1	0
Airq	1 if the PM2 level is less than 35 μg/m3	0.273	0.445	1	0
Pop_Den	1 if the Population density (people/km^2) $\leq$ 492,749; 0 otherwise	0.147	0.354	1	0
AvgPetrP	Average petrol price	6.711	1.126	9.960	5.290
AvgGDP	Average annual GDP per capita CHY	84,602.112	37,700.884	203,489	21,216
Covid-19	1 from January 2020 onwards; 0 otherwise	0.379	0.485	1	0
Movr	1 if restrictions on internal movements during Covid-19 are in place; 0 otherwise	0.264	0.441	1	0
Govsp	1 if the national government provides financial support during Covid-19; 0 otherwise	0.046	0.210	1	0
Purr	1 if purchase restrictions on conventional vehicles are in place; 0 otherwise	0.080	0.271	1	0
Drir	1 if conventional vehicles are subject to drive restrictions; 0 otherwise	0.148	0.355	1	0
Chan	Number of public chargers	38,800.372	69,286.792	563,175	19

4. Model Results

In addition to the methodological approach described in Section 3 (i.e., AS-SF), we also estimate an autoregressive stochastic production function (A-SF) without spatial affects entering into the functional form displayed in Equation (1). The model parameter estimates of both models are reported in Table 4. The log-likelihood function at convergence of the A-SF model is −11,799.914 with 20

Table 4
Model results.

	A-SF		AS-SF	
	Estimates	(z-value)	Estimates	(z-value)
Stochastic frontier estimates				
Intercept	−3.742	(−10.55)	−3.590	(−9.79)
Lagged direct EV sales	0.648	(97.68)	0.640	(92.66)
Lagged spatial EV sales	–	–	0.288	(3.55)
Lagged ICE vehicle direct effect	0.173	(17.87)	0.186	(17.93)
Lagged ICE vehicle spatial effect	–	–	−0.011	(−4.04)
EV charging stations direct effect	0.103	(9.11)	0.098	(8.58)
EV charging stations spatial effect	–	–	0.009	(3.94)
Summer	−0.120	(−4.97)	−0.120	(−4.96)
Low temperature dummy	−0.262	(−7.01)	−0.268	(−7.05)
Average petrol price	0.398	(4.32)	0.383	(4.06)
Population density $\leq$ 492,749k m2	−0.078	(−2.27)	−0.131	(−3.62)
Average annual GDP per capita	0.280	(10.2)	0.244	(8.29)
Air quality (PM2)	−0.113	(−4.22)	−0.106	(−3.87)
ICE purchase restrictions imposed	0.374	(7.81)	0.435	(8.75)
ICE driving restrictions imposed	0.152	(4.03)	0.138	(3.59)
Covid dummy	−0.316	(−8.64)	−0.332	(−8.99)
Covid movement restrictions	0.167	(4.97)	0.184	(5.44)
Efficiency estimates				
Central purchase subsidies	1.655	(11.78)	1.636	(11.16)
Local government contributions	0.654	(7.51)	0.611	(7.08)
EV charger subsidy	−0.742	(−7.14)	−0.764	(−6.88)
Covid financial government support provided	−0.718	(−2.37)	−0.623	(−2.09)
γ	0.841	(94.71)	0.839	(95.39)
Variance (σ_S^2)	3.000	(24.8)	2.984	(24.91)
Number of Cities	88		88	
Timeframe	95		95	
Number of observations	8360		8360	
Number of parameters	20		23	
Initial LL	−12,002.920		−12,002.920	
LL at convergence	−11,799.914		−11,784.490	
Bayesian Information Criterion (BIC)	23,780.452		23,776.698	
Akaike's Information Criterion (AIC)	23,639.828		23,614.980	

coefficients against -11,784.490 of the AS-SF with three additional parameters capturing spatial dependency. The log-likelihood ratio (LL-R) test can be used to compare the performance of the two models, as the A-SF is nested within the proposed AS-SF analysis (spatial parameters are normalized to zero). The estimated LL-R value is computed as 30.85 which is greater than the critical Chi-square value for three degrees at the one percent level. Hence, we can reject the null hypothesis and conclude that the AS-SF is the preferred model. A Moran's I test is also performed to verify the presence of spatial correlations within the data at hand (Yang et al., 2023). Because the estimated Moran's I statistic is positive, 0.368, and highly statistically significant (*p-value* < 0.01), we can assert that there exist significant positive spatial correlations at the city level in terms of EV sales. The presence of spatial correlation effects suggests that the estimation of a non-spatial structure would likely yield erroneous estimates, giving rise to misleading policy recommendations.

In what follows, we will therefore concentrate our attention on discussing the empirical findings that stems from the estimation of the AS-SF model. Finally, it is worth noting that the signs of coefficients obtained from SF models should be interpreted in an opposite manner to most other econometric models, including log-linear regression models. That is, a negative signed coefficient does not imply less EV sales, rather it suggests that the maximum possible EV sales are lower as the magnitude of the coefficient increases. As such, larger negative coefficients indicate the frontier reduces and becomes closer to the actual observed number of sales.

4.1. Estimates of the stochastic frontier component

The lagged parameter associated with EV sales is found to be statistically significant, suggesting that the sales of electric cars reported in the t^{th} month are highly influenced by the performance of the sector in the previous month (i.e., EV sales are stationary overtime), *all else being equal*. The lagged spatial parameter is also statically significant and positive, and as such, we can conclude that the sales volume of EVs within the same city is positively affected by the EV take-up rate of the neighbouring cities, *all else being equal* (Iogansen et al., 2023; Shi and Goulias, 2024). The latter finding confirms the existence of a strong spatial dependence across the demonstration cities that would be otherwise ignored by the A-SF model. Next, both the direct and the spatial effect estimates of ICE vehicle sales observed in *t-1* are statistically significant. Because the overall effect, calculated as $0.186 - 0.011 = 0.175$, is positive, we can deduce that the maximum level of potential EVs sellable in the t^{th} month augments as more traditional combustion engine cars are purchased, *all else being equal*. The fact that the spatial effect is found to be statistically significant but negative indicates that local policy interventions should be undertaken in such a way as to account for the negative spill-over patterns that arise from the sales of conventional vehicles in the neighbouring cities.

The increased provision of public charging stations for EVs within and near the city results in an overall increment of the EV sales frontier of approximately 0.107 percent, *all else being equal*. This result is line with what observed in Mukherijee and Ryan (2020), Sheng et al. (2022), He et al. (2022), and Pan, Uddin and Lim (2024). Both coefficients associated with summer and low temperatures are statistically significant and negative, suggesting that the sales of EVs are negatively influenced by extreme temperature levels (Yang et al., 2023; Li et al., 2023), *all else being equal*. The parameter associated with the average monthly petrol price is statistically significant and positive, suggesting that the increase of petrol price as a form of fuel tax would yield a growth of the EV sales frontier by around 0.38 percent (Vergis and Chen, 2015), *all else being equal*. Similarly, we find that the stochastic frontier of EV ownership appears to increase as the average GDP per capita increases (Sinton et al., 2024). On the other hand, cities with low population density are associated with a lower EV sales frontier, as shown by the negative and statistically significant coefficient (Chen et al. 2013; Xiong and Wang, 2020), *all else being equal*. Another interesting finding relates to the fact the frontier of EV sales appears to decrease with lower concentrations of PM2 in the air. It is important to highlight that this finding does not indicate that the adoption of EVs diminishes with a better air quality, but rather that the gap between the frontier and observed EV sales becomes smaller. A plausible explanation is that consumers appear to be less motivated to purchase fuel efficient cars if the air quality of the city they live in is perceived to be satisfactory. The introduction of driving and purchase restrictions on conventional vehicles seems to positively affect the maximum achievable EV sales. This indicates that such restrictions could have been more effectively leveraged to strengthen the EV adoption in the 88 pilot cities. Among the Covid-19 control variables, we report that cities that imposed restrictions on personal movements witness an increase in EV sales frontier, although the Covid-19 pandemic has a negative impact of the EV market growth.

4.2. Estimates of the efficiency component

The estimated model parameters within the technical inefficient component of the A-SF are of particular interest for this study. As shown in the table, the scale-back plan strategy for central purchase subsidies has a strong negative impact on the economic efficiency of the EV sector. This finding suggests that reinforcing financial incentives would have better sustain the promotion of fuel-efficient vehicles, particularly during the Covid-19 pandemic. Similarly, the remotion of local purchase subsidies is observed to negatively affect the EV sales efficiency in the period under examination. In contrast, the economic stimuli that local governments have introduced to improve the public charging infrastructure system are found to decreases the inefficiency of the emerging EV market. Further, financial support for households during the pandemic is also found to render the EV penetration more pervasive. The estimated

Table 5
Hypothesis testing for absence of inefficiency effects.

Null Hypothesis	Log-Likelihood at convergence	$\chi^2_{0.99}$	Test statistic
H0: $\gamma = \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 0$	−12,162	15.07	754.88

(a) Efficiency measures for 2016

(b) Efficiency measures for 2023

Fig. 1. Efficiency outputs by region for 2016–2023.

variance, σ_S^2, is reported to be statistically significant revealing the presence of heterogeneity in the EV sales across the 88 Chinese cities involved in the pilot project. Likewise, the γ parameter is statistically significant with an estimated value of 0.84. A γ value close to one indicates that inefficiency accounts for much of the variance present in the EV sales. Following Battese and Coelli (1995), it is possible to further undertake a LL-R test to verify whether there exists inefficiency in the EV market or not (Table 5). Under the null hypothesis, the four explanatory variables of the efficiency together with γ are assumed to be equal to zero, resulting in a log-linear model specification. The table shows that the hypothesis suggesting the absence of inefficiency effects in the model is rejected, given that the estimated test statistic is greater than $\chi^2_{0.99}$ with 5 degrees of freedom. This finding corroborates the importance of accounting for potential economic inefficiency when investigating the performance of the EV sector.

4.3. Analysis of EV market efficiency

Fig. 1 displays the efficiency outputs for each of the 88 pilot cities based on the AS-SF model for the years 2016 (Fig. 1a) and 2023 (Fig. 1b). Similar plots for the years 2017 to 2022 are available from the authors upon request. Of the 88 cities analysed as part of this study, for the year 2023, Haikou (0.733) and Chongqing (0.654) are the two most efficient cities with respect to EV sales, with Zhengzhou (0.652), Xi'an (0.647) and Xingtai (0.644) being placed third, fourth and fifth, respectively. The least efficient city in terms of EV sales is Chengde (0.268) followed by Sanming (0.351) and Zhangjiakou (0.372). Between 2016 and 2023, the efficiency of EV sales as measured by the AS-SF model improved for 77 of the 88 cities and declined for 11. Only 5 of the top 20 efficient cities in 2016 remain among the 20 most efficient cities in 2023. The most dramatic change in efficiency between 2016 and 2023 is for the city of Taiyuan, which drops from the first place to 17th. In contrast, the city of Zhengzhou shows the most remarkable improvement in terms of EV sales efficiency, with its score rising from 0.476 (ranked 18th) in 2016 to 0.652 in 2023 (ranked 3rd). The second and third best improvements are observed for the cities of Hefei and Xiamen also, which climb the EV sales efficiency ranking from 13th and 15th to 10th and 6th, respectively.

Fig. 2 illustrates the average efficiency measures for the years 2016 to 2023 across the 88 pilot cities, together with a moving average trend line of order 2. From the chart, we can observe a slight increase in the EV sales efficiency between 2016 and 2019, rising from 0.40 to 0.48. Subsequently, the penetration of the EVs seems to become more pronounced with efficiency reaching the value of 0.68 in 2021. The latter represents a 70 percent increment relative to the base year 2016. As displayed in the plot however, a decrease in efficiency seems to coincide with the Covid-19 pandemic, with the average efficiency dropping from 0.68 to 0.61 in 2022. This downward trend is estimated to persist in 2023, although the estimated average efficiency remains 10 percent higher than that reported four years earlier. Overall, the average efficiency in EV sales exabits a growth of approximately 35 percent compared to the beginning of the timeseries.

5. Model Applications

To understand the policy implications arising from the modelling exercise undertaken, based on the AS-SF model, we compute the number of EV sales forgone for each year over the eight-year time horizon, calculated as the difference between the predicted (representing total potential) and observed (actual) EV sales for each city. We further break down lost potential EV sales into lost sales of BEV and PHEVs. Assuming a perfect market substitution where a prospective buyer can purchase either ICE or electric cars, we postulate that the forecasted forgone BEV and PHEV sales represents the sale of ICE vehicles also. Under such an assumption and noting that EVs in China do not attract any government sales tax, whereas ICE vehicles attract an average sales tax of approximately five percent, it is possible to compute the gain in government revenue resulting from the sale of more petrol vehicles than otherwise should

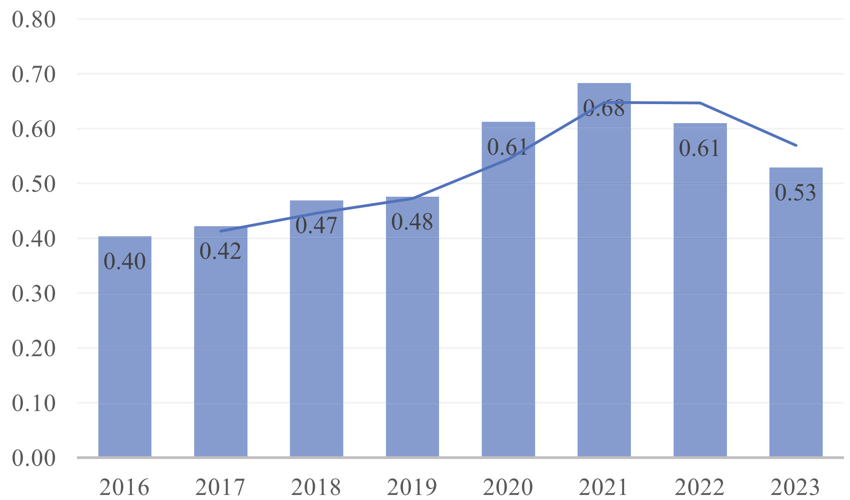

Fig. 2. Efficiency Plot 2016–2023.

have been the case. To calculate the additional government revenue obtained from the purchase of ICE cars as opposed to EVs, we apply a five percent tax rate to the average ICE vehicle price for each city known by month and year, and multiple this by the forecasted number of EV sales forgone. In addition to computing tax revenue, we are able to determine the amount of additional emissions generated from the purchase of ICE vehicles that could have been EVs. Assuming vehicles travel on average 11,600 kms per year, and petrol vehicles produce 134 g of CO2 per km travelled, PHEVs 68 g per km and BEVs zero grams per km travelled, knowing how many ICE vehicles were purchased that could have been BEV and PHEVs, we can calculate the total emissions that could have been saved in each year of the timeseries. Table 5 presents the results using the above approach applying the observed data for each of the 88 cities. Note that we use the observed market shares to calculate the potential loss of battery hybrid electric and battery electric vehicles.

As we can see from Table 6, 2017 represents the worse year in terms of lost potential EV sales, with 2021 being the best overall year. The poor performance of the EV market in 2017 and 2018 arose primarily due to potential BEV sales not occurring as opposed to PHEV, the market for which appears to operate closer to the efficient frontier. Perversely, assuming forgone EV sales were converted to ICE vehicles, the central government is estimated to have generated an additional ¥355,365,529.87 (US$49,000,642) in tax revenue over the eight-year period resulting from the fact that ICE vehicles attract a sales five percent tax that EVs do not. Nonetheless, the additional ICE vehicles sold generated 53,802 additional tones of CO2 gases that could have been avoided if the market was operating at the efficient frontier.

To test the impact of different policies on the EV market potential, we apply the AS-SF model to simulate three scenarios representing 1) the introduction of a ten percent tax on petrol, 2) a ten percent increase in the number of public chargers available, and 3) the introduction of policies to improve the air quality below 35 μg/m3for all 88 cities. The simulated scenarios are presented in Tables 7 to 9 respectively. Table 7 presents the modelled outcome assuming petrol prices were increased by 10 percent via the introduction of an environmental tax on petrol. The introduction of a 10 percent tax is predicted to have resulted in a greater number of EVs being sold than what actually occurred. Indeed, the loss in potential EV sales increases by an average of 1.08 for both BEV and PHEVs, with an additional 2,933 EV sales predicted to have occurred over the base model results. In addition to revenue raised from an increase of petrol costs by 10 percent resulting from the introduction of an environmental tax on petrol, the government benefited by ¥33,784,660.00 (US$4,658,499) in sales tax revenue that they would have lost over the same period had the policy been introduced. At the same time, if the vehicle market were operating at the efficient frontier, the increase in petrol prices would have reduced transport C02 emissions by 58,018 tonnes over the eight-year time frame examined, 4,5216 over the base scenario.

Table 8 presents the estimated outcome assuming the number of public charging stations in each of the 88 cities were increased by 10 percent over and above the number actually present. As with the petrol tax scenario, increasing the number of public charging stations available is predicted to increase the number of EV sales that would have occurred, widening the gap between the frontier and predicted sales. The potential market for EVs over the eight years would have been an additional 40,905 EVs, 3,608 more than under the base scenario. This represents an average market growth of 1.11 above the base scenario. The fact that the policy was not implemented resulted in a tax revenue of ¥389,150,190 (US$53,659,141) that the CG would have lost under a fully efficient market. Nonetheless, an additional 58,952 tonnes of CO2 entered the atmosphere than would have been the case had the market been operating at the efficient frontier and assuming the policy had been implemented.

Results from the third and final simulated scenario are given in Table 9. Under the third scenario, the air quality of all 88 cities is assumed to be improved to the highest standard measured. Under this scenario, the potential number of EV sales falls below the base case over the eight years, from 37,297 to 34,177 EVs, a decrease of 3,118 vehicles. The fact that fewer cars are predicted to be sold relative to the base scenario gives rise to a lost in government revenue raised via taxes on ICE vehicles of ¥29,700,158.97 (US$ 4,095,294), dropping from ¥355,365,530 (US$49,000,642) for the base to ¥325,665,371.03 (US $44,905,347) under the scenario being modelled. Finally, emissions are also predicted to be lower than predicted under the base scenario, decreasing from 58,018 tonnes of CO2 to 49,302 tonnes.

6. Discussion and Conclusions

This paper utilises an autoregressive spatial stochastic frontier model to explore the technical efficiency of the EV car market operating across 88 Chinese cities between the years 2016 and 2023. Inputs into the stochastic frontier model include variables

Table 6
Base outputs 2016 to 2023*.

Year	Lost potential EV sales	(BEV)	(PHEV)	Tax revenue not forgone	Tax revenue not forgone (US$)*	Emissions (tonnes)
2016	3,874	2,840	1,034	¥25,234,994.37	$3,479,602.90	5,206
2017	12,785	12,640	145	¥137,351,748.62	$18,939,157.91	19,759
2018	9,198	8,427	771	¥103,251,955.34	$14,237,205.62	13,689
2019	4,454	4,429	25	¥52,076,745.81	$7,180,758.33	6,904
2020	2,617	2,153	464	¥21,238,015.22	$2,928,467.44	3,702
2021	865	678	187	¥7,292,653.94	$1,005,569.47	1,197
2022	1,793	377	1,416	¥4,042,278.63	$557,381.72	1,670
2023	1,711	464	1,247	¥4,877,137.95	$672,498.80	1,676
Total	**37,297**	**32,008**	**5,289**	**¥355,365,530**	**$49,000,642**	**53,802**

* Yuan to US$ exchange rate of 0.139 as of 29 November 2024.

Table 7
Economic losses 2016 to 2023 assuming 10% tax on petrol*.

Year	Lost potential EV sales	(BEV)	(PHEV)	Tax revenue not forgone	Tax revenue not forgone (US$)*	Emissions (tonnes)
2016	4,152	3,047	1,105	¥27,100,992	$3,736,902	5,582
2017	13,733	13,577	156	¥147,510,906	$20,339,984	21,224
2018	9,919	9,088	831	¥111,325,245	$15,350,415	14,763
2019	4,803	4,777	26	¥56,184,387	$7,747,153	7,445
2020	2,839	2,337	502	¥23,092,824	$3,184,223	4,017
2021	976	768	208	¥8,266,694	$1,139,878	1,353
2022	1,948	409	1,539	¥4,404,221	$607,289	1,814
2023	1,859	504	1,355	¥5,295,972	$730,251	1,821
Total	**40,229**	**34,507**	**5,722**	**¥383,181,241**	**$52,836,095**	58,018

* Yuan to US$ exchange rate of 0.139 as of 29 November 2024.

Table 8
Economic losses 2016 to 2023 assuming 10% increase in the number of public chargers*.

Year	Lost potential EV sales	(BEV)	(PHEV)	Tax revenue not forgone	Tax revenue not forgone (US$)*	Emissions (tonnes)
2016	4,189	3,078	1,111	¥27,395,999.43	$3,777,580	5,635
2017	13,927	13,769	158	¥149,645,167.14	$20,634,273	21,523
2018	10,005	9,161	844	¥112,232,875.12	$15,475,567	14,886
2019	4,898	4,871	27	¥57,342,032.77	$7,906,778	7,592
2020	2,922	2,405	517	¥23,796,320.64	$3,281,227	4,134
2021	1,021	805	216	¥8,681,127.73	$1,197,023	1,417
2022	2,014	423	1,591	¥4,562,745.12	$629,148	1,876
2023	1,929	522	1,407	¥5,493,921.88	$757,546	1,889
Total	**40,905**	**35,034**	**5,871**	**¥389,150,190**	**$53,659,141**	58,952

* Yuan to US$ exchange rate of 0.139 as of 29 November 2024.

Table 9
Economic losses 2016 to 2023 assuming air quality improves to be below 35 μg/m3 for all 88 cities*.

Year	Lost potential EV sales	(BEV)	(PHEV)	Tax revenue not forgone	Tax revenue not forgone (US$)*	Emissions (tonnes)
2016	3,540	2,598	942	¥23,061,603.41	$3,179,918	4,760
2017	11,628	11,492	136	¥124,746,883.27	$17,201,098	17,967
2018	8,551	7,838	713	¥96,207,721.97	$13,265,890	12,729
2019	4,108	4,085	23	¥47,896,852.39	$6,604,401	6,367
2020	2,377	1,958	419	¥19,277,321.76	$2,658,111	3,364
2021	756	591	165	¥6,351,502.91	$875,796	1,045
2022	1,644	343	1,301	¥3,666,656.80	$505,588	1,529
2023	1,573	426	1,147	¥4,456,828.53	$614,543	1,540
Total	**34,177**	**29,331**	**4,846**	**¥325,665,371.03**	**$44,905,347**	49,302

* Yuan to US$ exchange rate of 0.139 as of 29 November 2024.

associated with whether or not local or central government subsidies are made available to residents of various cities for the purchase and operation of EVs, the number of public EV charging stations are present, the average temperature of each city, the occurrence of the summer season, and the amount of pollution recorded at each location. Other inputs into the model comprise average petrol prices, population densities, GDP per capita, as well as various variables representing different restrictions and/or subsidies associated with Covid-19.

The empirical findings reveal a strong autoregressive nature in the EV market with sales registered in previous months being highly correlated with current sales. The significant presence of spillover effects whereby the sales volume of EVs from one city are positively correlated with the sales volumes of neighbouring cities in the previous month indicates a notable spatial dependence across the 88 demonstration cities. In this regard, interventions such as the upgrade of the existing EV charging public system is likely to positively drive the demand for EVs not only within the city but also in the neighbouring areas. As discussed in Iogansen et al. (2023), consumers are more likely to purchase EVs when they are exposed to a greater number of electric cars and related EV infrastructure. Both direct and spatial effects associated with ICE vehicle sales in previous months are also detected, with a positive overall effect estimated, indicating that across the 88 cities examined, cities with greater numbers of traditional ICE vehicles have a greater potential to sell a larger number of EVs. Unlike the positive impact EV sales have on neighbouring cities however, we found that the spatial effect associated with conventional vehicles is negative, meaning that any policies implemented that are designed to promote EV sales in one city should also account for potential spill-over effects of policies that impact the sale of conventional vehicles in neighbourhood cities.

Our empirical investigation also highlights that cities with a greater number of public charging stations available increase the frontier for EV sales. On the other hand, the scale-back structure of purchase subsidies negatively impacts the efficiency of the EV sector suggesting that a different intervention strategy could have potentially resulted in more EVs on roads over the period under study. In similar vein, we report that local government financial contributions also imper the efficiency of the market.

Of some interest is the finding that frontier of EVs appears to be negatively influenced by improved air quality. We propose that this outcome may be the result of residents in less polluted cities being less motivated to purchase an EV than residents living in more polluted locations. Petrol prices and population density also increase the EV sales frontier. Finally, it appears that the efficiency of the Chinese EV market has on average diminished since the advent of Covid in 2019.

As part of the paper, we also performed a simulation exercise to test the efficacy of three policies on the efficiency of the Chinese EV market. Of the three policies, increasing the number of public chargers by 10 percent was found to have a larger impact on improving the efficiency of the EV market across the 88 cities, more so than both implementing a fuel tax on petrol of 10 percent and improving the overall air quality experienced within each city. Indeed, as noted earlier, the modelling undertaken suggests that improving air quality makes the EV market less efficient than otherwise has been the case. In testing each of the three scenarios, we further examined the impact on both government revenue derived from sales taxes on conventional fueled vehicles as well as the amount of CO2 released into the atmosphere. Perversely, given that no sales taxes are imposed on EVs, increasing the efficiency of EV sales negatively impacts on revenue streams, thus providing somewhat of a disincentive for government to persevere with policies designed to promote EV additional sales. A potential government intervention to make up the loss of revenue from fuel taxation could be the implementation of a per-km charge (or road usage charge) for EVs, given that they are not currently subject to any taxation. Another alternative could be to increase the cost of charging at public government owned charging outlets, with the revenue generated being used to finally support infrastructure improvements. A further result of the policy evaluation exercise is that improved air quality negatively impacts the efficiency of EV markets, any non-transport related policies introduced by government designed to improve air quality runs the risk of limiting EV sales, and hence increases transport related emissions. Further yet, if such a relationship between air quality and EV sales continues to exist into the future, it is possible that as transport related emissions decreases as a result of a greater number of EVs being sold relative to ICE powered vehicles, then the sale of Ice vehicles will increase, resulting in greater long-term pollution occurring. As such, more forceful interventions may need to be imposed such as restrictions on ICE vehicle sales or usage, if such a viscous cycle is to be avoided.

This paper contributes to the current literature on the topic in two ways. First, this study utilizes for the first time a stochastic frontier model to quantify the latent (unobserved) sales frontier of the EV market whilst also accounting for potential spatial patterns. The features of the spatial based stochastic frontier are herein exploited to uncover interesting insights that originate from the impact of government interventions on the Chinese car market of 88 pilot cities between the years 2016 and 2023. Second, unlike previous applications, the data on EV sales span a longer period of time up to 2023 alongside the fact that additional variables have been addended, the most important of them is the electric vehicle charging availability (see, for example, Sheng et al., 2022).

Whilst this study investigates the evolution of the EV market from the novel perspective of the sales efficiency, there are some limitations that need to be acknowledged. The first limitation relates to the absence of some policy variables such as parking discounts or access to HOV lanes from the set of inputs employed for estimation. The inclusion of such variables could have assisted us in measuring the stochastic frontier for EV sales in a more accurate manner. This limitation can be primarily attributable to the challenges that the data collection process consisting of the consultation of a wide range of sources place upon the analyst. The second limitation refers to the fact that we are only able to account for spatial patterns that originate from policy interventions introduced in the 88 cities taking part in the demonstration project. This somewhat provides a partial accounting of the underlying spatial dependence as we fail to capture the potential impact that structural reforms deployed in neighboring cities not belonging to the demonstration project might have on the sales of EVs occurred in the demonstration ones.

CRediT authorship contribution statement

Andrea Pellegrini: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Xusheng Yao:** Data curation, Funding acquisition, Visualization, Writing – original draft, Writing – review & editing, Formal analysis. **John M. Rose:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Shoufeng Ma:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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