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

ABSTRACT: 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 2021. 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 scrutiny 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 assessment 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 introducing a 10 percent environmental tax on petrol would have resulted in the sales of around 71,000 EVs more across the 88 cities over six years.

KEY WORDS: ***Electric vehicle uptake, Stochastic frontier, Spatial effects, Policy reforms, China***

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1. INTRODUCTION

The threat of global warming on human health has led international and national governments to implement a series of 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 (Avci et al., 2015; Zhang et al., 2013; IEA, 2015). In 2019, the International Energy Agency (IEA) quantified that worldwide, transportation related emissions made up 27 percent 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, 2019). Given 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 (Jang and Choi, 2021; Nanaki and Koroneos, 2016; Yu and Stuart, 2017).

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 (Araújo et al., 2019; Ghasri et al., 2021; Girard et al., 2019; Masuda et al., 2017). 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 global EV market has rapidly expanded with the total EV sales growing from 120,000 to 6.6 million units in 2021, almost doubling between 2020 and 2021 (IEA, 2021). Despite the negative effects of the Covid-19 pandemic and microchip shortages, China continues to be by far the market leader with more than 3.5 million electric cars sold in 2021 (around 53 percent of global EV sales). Of these newly registered EVs, 82 percent were classified as BEVs with the remaining 18 percent reported to be PHEVs. China's electric vehicle fleet currently amounts to over 7.8 million cars which is more than twice that of 2019 prior to the Covid-19 outbreak (IEA, 2020). The impressive development of the Chinese EV market is largely attributable to the great variety of economic policies set out by the General Office of the State Council (GOSC). In 2021, for example, the GOSC announced the *14th Five-Year Plan (FYP) 2021-2025* which comprises a wide range of initiatives specifically design to consolidate the penetration of the EVs into the Chinese market. 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, 2022).

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; Pellegrini and Rose, 2023). 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 (Cherchi, 2017; Chorus et al., 2013; Hackbarth and Madlener, 2013; Hess et al., 2012; Hidrue et al., 2011; Hoen and Koetse, 2014). 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. Potuglou and Kanaroglou (2007) found 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) (2008) report 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). Caufield et al. (2010) point 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) suggest that government rebates on energy bills and parking costs would strengthen the EV diffusion in Australia. Recently, 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.

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. 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. 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 to examine the effectiveness of different policies put into action by the Chinese government, suggesting that the introduction of restrictions on conventional vehicle purchases positively influenced the promotion of EVs (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, finding that both charging discount and infrastructure construction subsidy were found to be pivotal for the market breakthrough of EVs (Ou et al., 2020), whereas the provision of purchase incentives had no effect on EV sales. Finally, 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.

This study seeks to contribute to the stream of the transportation literature that utilizes aggregate level econometric methods to measure the influence of government policies on the decision of buying an EV. To do so, we fit monthly sales data collected from January 2016 to December 2021 in 88 demonstration cities in China (see, for further details, Yao et al., 2022) with an autoregressive spatial stochastic frontier (SF) model (Aigner et al., 1977; Battese and Coelli, 1995). In 2009, the Chinese government announced the *Ten Cities and Thousand Vehicles* project which aimed at reaching the sale of at least 1,000 EVs in each targeted city via the provision of a one-off purchase subsidy (OECD, 2009). After three years, the Chinese Central Government (CCG) launched the second demonstration project bringing the overall number of pilot cities to

88, with the ultimate goal to further strengthen the promotion of electromobility in China. Unlike previous research studies such as Chi et al. (2021) and Yao et al. (2022) who looked at data from the same 88 cities, the proposed spatial-temporal SF approach applied here allows for quantifying the maximum level of sales (i.e., frontier) that each pilot city could have possibly achieved in the timeframe under evaluation 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. The underlying assumption is that 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 the EV market in each pilot city is efficient. Further, the use of a spatial structure is essential within this context of application insofar as it accommodates the potential impact of spill-over effects on the unobserved frontier of EV sales arising from similar policy reforms introduced in neighbouring areas (see, for example, Sheng et al., 2022).

The reminder of the paper is structured as follows. The next section illustrates the dependent and input variables used in this study, whereas Section 3 presents the features of the employed SF approach. 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. DATA

This section provides a detailed description of the variables that we adopt for the estimation of the stochastic frontier model. 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 2021. In order to better understand the evolution of the EV market, Table 1 displays the aggregate annual sales of EVs and conventional vehicles (*Salcv*) for the timeframe under scrutiny, respectively. From the table, it emerges that the sales volume of EVs rapidly increased from 2016 to 2021 reaching the milestone of 1,936,097 units sold in 2021, albeit after exhibiting a significant drop between the years 2018 and 2019 (-6.9 percent year on year). Since the beginning of the timeseries, the vast majority of newly registered EVs are battery electric cars with the highest number of sales being registered in 2021 with more than 1,500,000 automobiles sold (+ 60.1 percent compared to the year before). 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 2020-2021, however, the sales of PHEVs reached 480,330 units, approximately three-quarters of which were sold in 2021 alone. Overall, EVs made up 15 percent of all automobiles sold across the 88 pilot cities, with an annual average market share of 5.46 percent.

Table 1: Vehicle Sales in 88 prefecture-level cities from 2016 to 2021

	Timeframe of the current study					
Fuel type	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
BEVs	169,995	378,961	576,032	538,655	636,526	1,593,799
PHEVs	2,194	2098	12,052	953	138,032	342,298
ICE Vehicles	14,759,789	14,855,033	13,994,350	13,355,349	12,461,062	13,303,363

The input variables used in the empirical analysis can be broadly grouped into four categories. The first category comprises three variables representing the financial policies that the Chinese Central Government (CGC) has implemented in order to stimulate EV purchase and usage. These include central (government) financial purchase subsidies (*Cenfs*), local (government) financial purchase subsidies (*Locfs*), and local (government) financial charger subsidies (*Chas*). The *Cenfs* were designed by the CCG so 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 2021. 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 kilometres (km) benefited from a discount of 25,000 CHY ($3,750 USD), whereas one with a driving range of more than 250 km was subject to a discount of 55,000 CHY ($8,250 USD). However, the maximum purchase rebate available in 2021 amounted to only 18,000 CHY ($2,750 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 ($4,500 USD) in 2016 to 6,800 CHY ($ 1020 USD) in 2021.

Table 2: Central government's financial subsidy in 2016-2021

Time	National subsidy for EV and PHEV
2016	**BEV:** 100≤R<150:2.5;150≤R<250:4.5; R≥250:5.5. **PHEV:** R≥50:3.
2017	**BEV:** 100≤R<150:2;150≤R<250:3.6; R≥250:4.4. **PHEV:** R≥50:2.4.
2018	**BEV:** 150≤R<200:1.5;200≤R<250:2.4;250≤R<300:3.4;300≤R<400:4.5; R≥400:5. **PHEV:** R≥50:2.2.
2019	**BEV:** 250≤R < 400:1.8; R≥ 400:2.5. **PHEV:** R≥50:1.
2020	**BEV:** 300≤R < 400:1.62; R≥ 400:2.25. **PHEV:** R≥50:0.85.
2021	**BEV:** 300≤R < 400:1.3; R≥ 400:1.8. **PHEV:** R≥50:0.68.

* 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).

In order to stimulate the mass diffusion of EVs, local political authorities made available additional subsidies for the purchase of EVs, *Locfs*, as well as funds for the installation of recharging stations for EVs, *Chas*. With respect to the *Locfs*, the CCG announced in 2017 that the financial stimuli provided by local authorities could not exceed 50 percent of the value of *Cenfs*. As shown in Figure 1, the number of pilot cities that provided incentives for the construction and operation of public charging stations grew from 49 to 75 in 2021, with the best year being 2020 with 80 out of 88 cities taking part in the demonstration project investing in the strengthen of the public charging network.

The second category of inputs encompasses two variables describing the restrictions introduced to slow down the proliferation of conventional passenger vehicles, namely *Purr* and *Drir*. While *Purr* represents the restrictive measures imposed to limit the purchase of ICE vehicles, *Drir* relates to driving restrictions applied to ICE vehicles on some roads of the pilot cities.

The third category comprises variables describing the socio-economic and environmental characteristics of each pilot city. Specifically, summer (*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. Similarly, temperature (*Temp)* takes the value of one if the average monthly temperature is reported to be below zero, and zero otherwise. A dummy variable representing the concentration of PM2 in the air, *Airq*, was also included in the modelling specification, with *Airq* taking the value of one if the average PM2 level recorded is less than 35 µg/m3, and zero otherwise. Three continuous variables also belong to this category. These are average monthly petrol price (*AvgPetrP*), population density expressed as the number of people per square meter (*Pop_Den*), and average annual GDP per capita (CHY) reported at the city level.

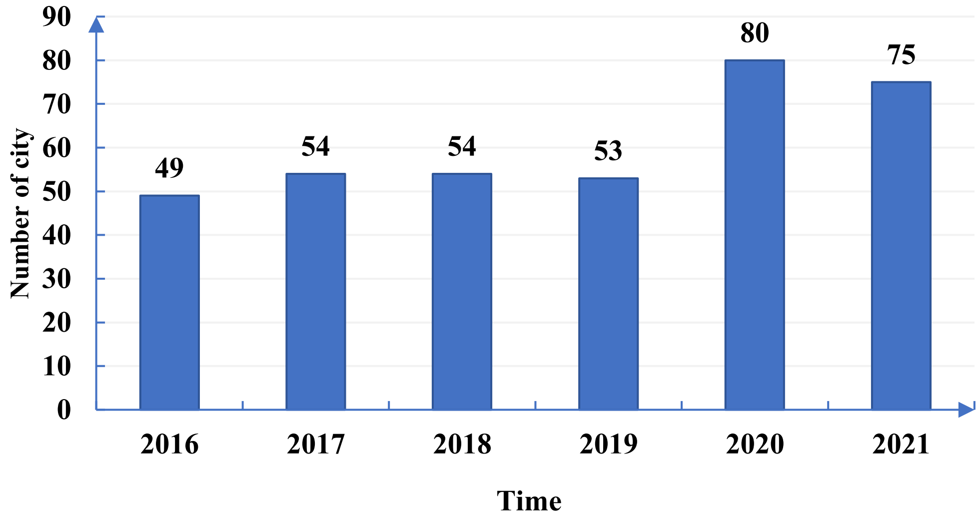


Figure 1: Number of the city which provide subsidies for the construction/operation of public chargers

The fourth and final group includes four variables that account for the impact of Covid-19 on the sales of EVS, with these variables being designated *Movr*, *Pubec*, *Govsp* and *Covid-19*. *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. *Pubec* takes the value of one if public events and social gatherings were forbidden at the city level, and zero otherwise. The third variable, *Govsp*, denotes whether the CCG provided income support to households during the pandemic or not. The last variable, *Covid-19*, is a dummy variable representing the start of the Covid-19 pandemic (*Covid-19* takes the values of one from January 2020 onwards, and zero otherwise).

Finally, two additional variables are embedded within the set of inputs, conventional vehicle sales (*Salcv*) and number of public chargers (*Chan*). *Salcv* is used to capture the effect of conventional vehicle purchases on the EV market, whereas *Chan* captures the growth of the public EV charging points available at the province level. Table 3 depicts the ten provinces belonging to the demonstration project with the largest number of public chargers. The provinces of Henan and Zhejiang, for example, increased the provision of public charger stations by 97.5 percent over six years, whereas Hebei and Hubei showed a growth of 95 percent and 94.5 percent, respectively. Overall, the average increase in the public EV charger amount is approximately 93 percent across the ten Chinese provinces listed in Table 3.

Table 3: Top 10 pilot cities with the largest number of public chargers

Province	# Public chargers in January 2016	# Public chargers in December 2021	% of growth
Guangdong	11876	111226	89.3%
Shanghai	5202	81382	93.6%
Beijing	9027	78933	88.6%
Jiangsu	7170	72165	90.1%
Zhejiang	1505	60762	97.5%
Shandong	3814	47012	91.9%
Anhui	3915	39273	90.0%
Hubei	2003	36194	94.5%
Henan	728	29353	97.5%
Hebei	1422	28177	95.0%

2.1 Data collection and descriptive statistics

The dependent (*Salev*) and input variables are collected on a monthly basis for each pilot city between January 2016 and December 2021. The corresponding descriptive statistics across the 88 cities over the six years for which data are captured are given in Table 4. Both sales of EVs (*Salev*) and conventional vehicles (*Salcv*) are obtained from the Traffic Management Bureau office of the pilot city under. From Table 4, there exists a divergence in the monthly sale volumes between electric and conventional vehicles, with the maximum number of fuel-efficient cars sold being 30,958 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 0.39 and 0.69, 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 (www.weather.com.cn), whereas the China Air Quality Online Monitoring and Analysis Platform (www.aqistudy.cn) and the Oriental Fortune (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 2016-2021 China Urban Statistical Yearbook. Table 4 depicts that the average population per meter square is approximately 1,107.069 with a standard deviation of 842.381, whereas the maximum petrol price over the six-year period stands at CHY 9.053 per litre. To control for the impact that the ongoing Covid-19 pandemic has on consumer purchase behaviour, *Movr, Pubec, and Govsp* were created based upon information available on the Oxford Covid-19 Government Response Tracker website (www.bsg.ox.ac.uk/research/covid-19-government-response-tracker). As discussed previously, a further dummy variable, *Covid-19*, entered into the model as a proxy for the start of the Covid-19 pandemic. Finally, we assembled data on the number of public chargers (*Chan*) by examining the China Electric Vehicle Charging Infrastructure Promotion Alliance website (www.evcipa.org.cn).

Table 4: Descriptive statistics

Variables	Variables Definition	Mean	S.D.	Max.	Min.
Salev	Sales of PHEVs and BEVs	693.118	1,924.576	30,958	0
Salcv	Sales of conventional vehicles	12,363.850	12,255.110	106,410	0
Cenfs	Central government financial purchase subsidies (2016 is base)	0.569	0.287	1	0.227
Locfs	1 if local government provide financial purchase subsidies; 0 otherwise	0.390	0.488	1	0
Chas	1 if local government provides subsidies for construction/operation of public chargers; 0 otherwise	0.691	0.462	1	0
Sumr	1 if the season is summer (June, July and August); 0 otherwise	0.250	0.433	1	0
Temp	1 if the temperature is below 0; 0 otherwise	0.090	0.286	1	0
Airq	1 if the PM2 level is less than 35 µg/m3	0.159	0.366	1	0
AvgPetrP	Average petrol price	6.581	0.629	9.053	5.290
Pop_Den	Population density (people/km^2)	1,107.069	842.381	6,814,815	115,610
AvgGDP	Average annual GDP per capita CHY	91,728.530	36,661.030	203,489	21,216
Covid-19	1 from January 2020 onwards; 0 otherwise	0.333	0.471	1	0
Movr	1 if restrictions on internal movements during Covid-19 are in place; 0 otherwise	0.252	0.434	1	0
Pubec	1 if public events and gatherings are forbidden during Covid-19; 0 otherwise	0.247	0.431	1	0
Govsp	1 if the national government provides financial support during Covid-19; 0 otherwise	0.151	0.363	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	19,265.960	25,176.350	181,846	19

3. METHODOLOGY

In this section, the autoregressive spatial stochastic frontier (henceforth, AS-SF) model (Aigner et al., 1977; Battese and Coelli, 1995), that represents the core of tool used for analysis within this paper. Several studies so far have employed SF methods to carry out 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 measured the technical efficiency of the world's largest container ports (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 calculating the effect of airline market concentration on airport technical efficiency in Spain, whereas Pinjari et al. (2016) exploited the features of the SF to determine the unobserved time budget within a context of time-use allocation decisions (see, also, Pellegrini et al., 2021, for an application on expenditure behaviour).

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

$$Y_{it} = \exp\left(x_{it}\beta + V_{it} - U_{it}\right), \tag{1}$$

where Y_{it} corresponds to the number of electric cars sold by the pilot city i ($i = 1, \dots, I$) in the t^{th} month ($t = 1, \dots, T,$), x_{it} is a $(1 \times l)$ vector of values of input variables describing the pilot city i in the t^{th} month, β is a $(l \times 1)$ vector of unknown parameters to be estimated, 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 $t = 1, \dots, T$ and $i = 1, \dots, I$. 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, σ^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 $\Lambda_{it} \sim N(0, \sigma^2)$, is specified such that the point of truncation is defined as $\Lambda_{it} \geq -f_{it}\alpha$. 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. Next, the density function for the Y_{it} as expressed in Equation (1) is given by

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

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

Then, the logarithm of the likelihood function for the sample observations $y = (y'_1, y'_2, \dots, y'_T)'$ can be written as

$$\begin{aligned} L = (\delta; y) = &-\frac{1}{2}\sum_{i=1}^{I} t_i \left[\ln(2\pi) + \ln(\sigma_V^2 + \sigma^2)\right] \\ &-\frac{1}{2}\sum_{i=1}^{I}\sum_{t=1}^{T_i}\left[\frac{(y_{it} - x_{it}\beta + f_{it}\alpha)^2}{\sigma_V^2 + \sigma^2}\right] \end{aligned} \tag{3}$$

$$-\frac{1}{2}\sum_{i=1}^{I}\sum_{t=1}^{T_i}[\ln(\Phi(d_{it}) - \Phi(d_{it}^*))],$$

where $\delta = (\beta, \alpha, \sigma_V^2, \sigma^2)$.

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:

$$
\begin{aligned}
L = (\delta; y) = &-\frac{1}{2}\sum_{i=1}^{I} t_i\,[\ln 2\pi + \ln(\sigma_S^2)] \\
&-\frac{1}{2}\sum_{i=1}^{I}\sum_{t=1}^{T_i}\left[\frac{(y_{it} - x_{it}\beta + f_{it}\alpha)^2}{\sigma_S^2}\right] \\
&-\frac{1}{2}\sum_{i=1}^{I}\sum_{t=1}^{T_i}[\ln(\Phi(d_{it}) - \Phi(d_{it}^*)],
\end{aligned}
\tag{4}
$$

where $d_{it} = \frac{f_{it}\alpha}{\sqrt{\gamma\sigma_S^2}}$, $d_{it}^* = \frac{\mu_{it}}{\sqrt{\gamma(1-\gamma)\sigma_S^2}}$, $\mu_{it} = (1-\gamma)f_{it}\alpha - \gamma(y_{it} - x_{it}\beta)$, $\sigma = \sqrt{\gamma(1-\gamma)\sigma_S^2}$.

The method of maximum likelihood is used to simultaneously estimate the vector of unknown parameter $\delta = (\beta, \alpha, \sigma_S^2, \gamma)$, 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.

3.1 Model specification

Numerous model structures were explored with the AS-SF formalised in Equations (6-7) representing the final model specification.

$$
\begin{aligned}
\ln(Salev_{it}) = \beta_0 \\
&+(\rho + \lambda W)\ln(Salev_{it-1}) + (\beta_1 + \beta_{1W}W)\ln(Salcv_{it-1}) \\
&+ (\beta_2 + \beta_{2W}W)\ln(Chan_{it}) \\
&+ \beta_3\ln(Cenfs_{it}) + \beta_4\,(Locfs_{it}) \\
&+ \beta_5\,(Sumr_{it}) + \beta_6\,(Temp_{it}) + \beta_7\,(Airq_{it}) + \\
&\beta_8\,(AvgPetrP_{it}) + \beta_9(Pop_{Den_{it}}) + \beta_{10}(AvGDP_{it}) \\
&+ \beta_{11}(Covid-19_{it}) + \beta_{12}(Movr_{it}) + \beta_{13}(Pubec_{it}) \\
&+ V_{it} + \mathrm{U}_{it},
\end{aligned}
\tag{6}
$$

and

$$\mathrm{U}_{it} = \alpha_1\,(Govsp_{it}) + \alpha_2\,(Purr_{it}) + \alpha_3(Drir_{it}) + \alpha_4\,(Chas_{it}), \tag{7}$$

where ln represents the natural logarithm, and $-1 \leq \rho \leq 1, 0 \leq \lambda \leq 1$.

In the above equations, i denotes the index related to the i^{th} pilot city with $i = 1, \dots, 88$ whilst t refers to the t^{th} month with $t = 2, \dots, 72$. The timeframe for analysis spans 71 months beginning from February 2016 (*t=2*) to December 2021 (*t=72*) 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. To this end, three spatial variables were incorporated into Equation (6). These are

$$\begin{aligned} &W \ln(Salev_{it-1}), \\ &W \ln(Salcv_{it-1}), \\ &W \ln(Chan_{it}), \end{aligned} \tag{8}$$

where W consists of a (88×88) weighted adjacency matrix which can be written as below,

$$W = \begin{bmatrix} 0 & w_{12} & w_{13} & w_{14} & \dots & w_{1I} \\ w_{21} & 0 & w_{23} & w_{24} & \dots & w_{2I} \\ w_{31} & w_{32} & 0 & w_{34} & \dots & w_{3I} \\ w_{41} & w_{42} & w_{43} & 0 & \dots & w_{4I} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ w_{I1} & w_{I2} & w_{I3} & w_{I4} & \dots & 0 \end{bmatrix} \tag{9}$$

A rock contiguity algorithm was employed to compute the weights (w_{ii} with $i = 1, \dots, 88$) of the distance matrix W (Equation (9)), 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.

4. RESULTS

In addition to the methodological approach outlined in the previous section (i.e., AS-SF), we also estimate an autoregressive stochastic production function (A-SF) in which the presence of neighbourhood patterns is not accounted for. The model parameter estimates of both models are reported in Table 6. The log-likelihood function at converge of the A-SF model is -9518.166 with 21 coefficients whilst that of the AS-SF is -9501.647 with three additional parameters representing the spatial dependence across the pilot cities. Given that the the A-SF model is nested within the AS-SF model (in the former model, the spatial parameters are set to zero), we can compare the two by means of the log-likelihood ratio test (LL-R). The LL-R value between the AS-SF and A-SF models is computed as 33.038 which is greater than the critical Chi-square value for three degrees at the 0.005 percent level. Based upon the statistical evidence, we can reject the null hypothesis and conclude that the proposed AS-SF is the preferred model. As such, in what follows, attention is placed on describing the empirical findings of the AS-SF model outputs. Given that the continuous variables are expressed in logarithmic form, the corresponding estimated parameters can be directly interpreted as elasticity measures. Further, 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. 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.

Table 6: Model results

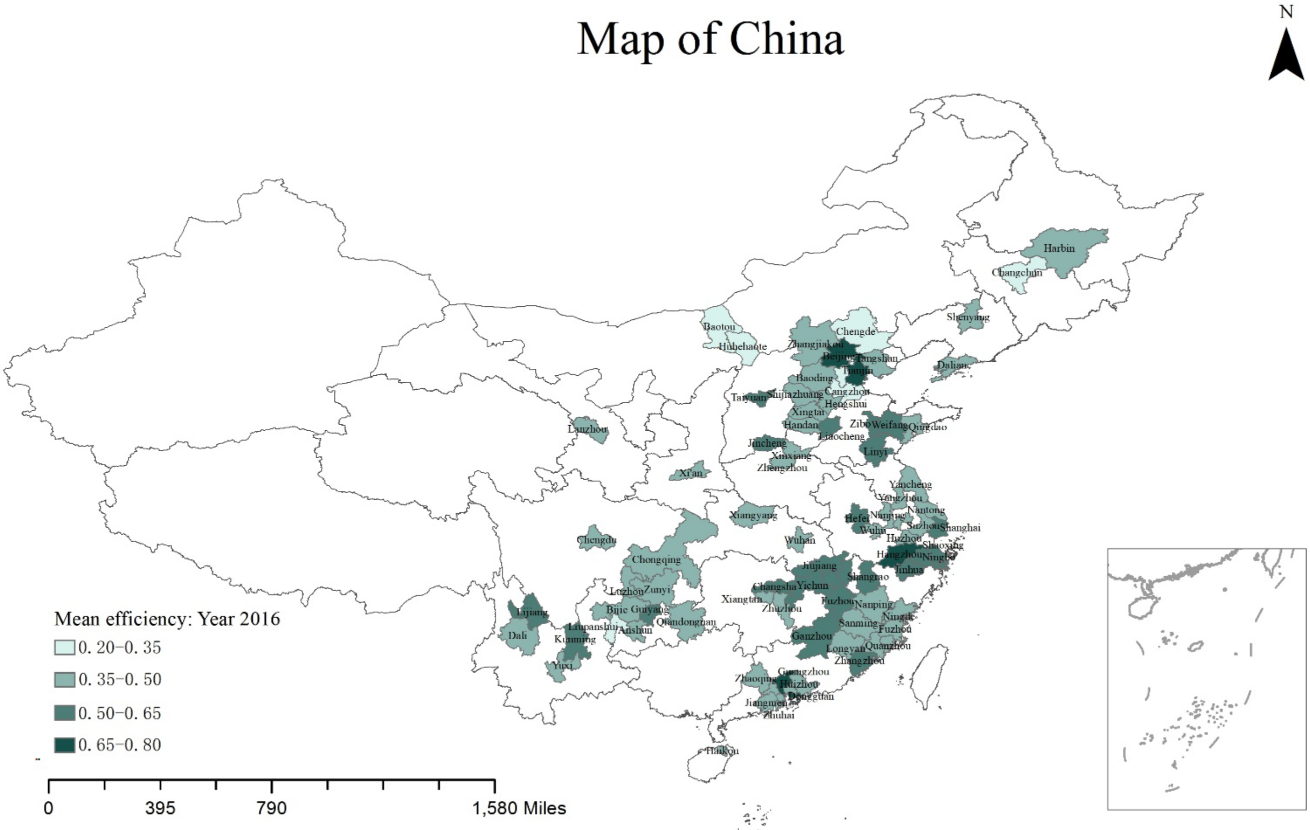
	A-SF		AS-SF	
	Estimates	(z-value)	Estimates	(z-value)
Constant (β_0)	-3.803	(-7.30)	-3.555	(-6.75)
Lagged log(direct EV sales) (ρ)	0.934	(69.95)	0.939	(67.81)
Lagged log(spatial EV sales) (λ)	-	-	0.731	(2.25)
Lagged log(ICE vehicle direct effect) (β_1)	0.150	(10.43)	0.173	(11.56)
Lagged log(ICE vehicle spatial effect) (β_{1W})	-	-	-0.019	(-5.05)
Log(EV charging stations direct effect) (β_2)	0.123	(8.05)	0.120	(7.81)
Log(EV charging stations spatial effect) (β_{2W})	-	-	0.018	(5.29)
Central purchase subsidies (β_3)	-0.280	(-4.63)	-0.228	(-3.70)
Local government contributions (β_4)	0.278	(6.76)	0.289	(7.04)
Summer (β_5)	-0.132	(-4.14)	-0.131	(-4.11)
Low temperature dummy (β_6)	-0.243	(-4.82)	-0.238	(-4.67)
Air quality (PM2) (β_7)	-0.142	(-3.93)	-0.150	(-4.08)
Average petrol price (β_8)	1.077	(6.46)	1.012	(6.01)
Population density (β_9)	0.169	(7.52)	0.197	(8.53)
Average annual GDP per capita (β_{10})	0.042	(1.11)	0.003	(0.07)
Covid dummy (β_{11})	0.057	(0.75)	0.052	(0.68)
Covid movement restrictions (β_{12})	0.275	(4.62)	0.277	(4.64)
Covid public gathering restrictions (β_{13})	-0.085	(-1.44)	-0.081	(-1.38)
Covid financial government support provided (α_1)	-1.058	(-3.25)	-1.101	(-3.39)
ICE purchase restrictions imposed (α_2)	-2.652	(-6.43)	-2.708	(-6.50)
ICE driving restrictions imposed (α_3)	-0.369	(-2.10)	-0.316	(-1.83)
EV charger subsidy (α_4)	-0.475	(-4.28)	-0.445	(-3.88)
Variance (σ_S^2)	2.874	(28.15)	2.841	(27.15)
Inefficiency effect (γ)	0.787	(61.58)	0.786	(55.79)
Number of Cities	88		88	
Timeframe	71		71	
Number of observations	6248		6248	
Number of parameters	21		24	
Initial LL	-10218.490		-10218.490	
LL at convergence	-9518.166		-9501.647	
Bayesian Information Criterion (BIC)	19219.872		19213.054	
Akaike's Information Criterion (AIC)	19078.332		19051.294	

The autoregressive parameter, ρ, is estimated to be statistically significant and close to one, suggesting that the sales of electric cars reported in the t^{th} month are highly influenced by the sales in period *t-1*, *all else being equal*. λ is statistically significant and equal to 0.70 indicating that the sales volume of EVs within the same city is positively affected by that reported in the neighbouring cities in the previous month, *all else being equal.* 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, the direct effect (β_1) and the spatial effect (β_{1_W}) estimates pertaining to ICE vehicle sales observed in *t-1* are both statistically significant. The overall effect, calculated as $0.173\ (\beta_1) - 0.019\ (\beta_{1_W}) = 0.154$, is positive and hence we conclude that as the number of traditional vehicles on roads increases, so too the maximum level of potential EVs sellable in the next period t, *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. This is consistent with a study undertaken by Ioganssen et al. (2023) who found that consumers are more likely to purchase EVs when they are exposed to a greater number of electric cars and related EV infrastructure The coefficients β_2 and β_{2W} are statistically significant and positive, suggesting that the increase provision of public charging stations for EVs within and near the city results in an overall increment of the EV sales frontier of approximately 0.138 percent, *all else being equal*. As for central purchase subsidies, the corresponding parameter β_3 is statistically significant and negative, suggesting that the scale-back plan implemented by the CCG negatively impacts the maximum achievable sales frontier for fuel-efficient cars. On the other hand, financial contributions offered by local governments, β_4, generates an increment of the frontier of about 0.289 percent, *all else being equal*. β_5 and β_6 are both statistically significant and negative, indicating that both summer and low temperatures negatively impact the EV sales frontier. Another interesting finding relates to the fact the demand for EVs appears to be negatively influenced by the low concentration of PM2 in the air (β_7). This perhaps reflects the fact 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 parameter associated with the average monthly petrol price, β_8, 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 1.012 percent. Similarly, we find that densely populated cities tend to positively impact the EV market penetration as shown by the positive and statistically significant β_9 coefficient. Also included in the model is a parameter associated with the average GDP per capita. The parameter for this variable is not statistically significant suggesting that the overall level of economic growth for the country does not impact on EV sales. Among the Covid-19 control variables, we found that cities that imposed restrictions on personal movements witnessed an increase in EV sales, whilst both the imposition of restrictions on public gatherings and the advent of the Covid-19 did not show a direct impact on the EV sales.

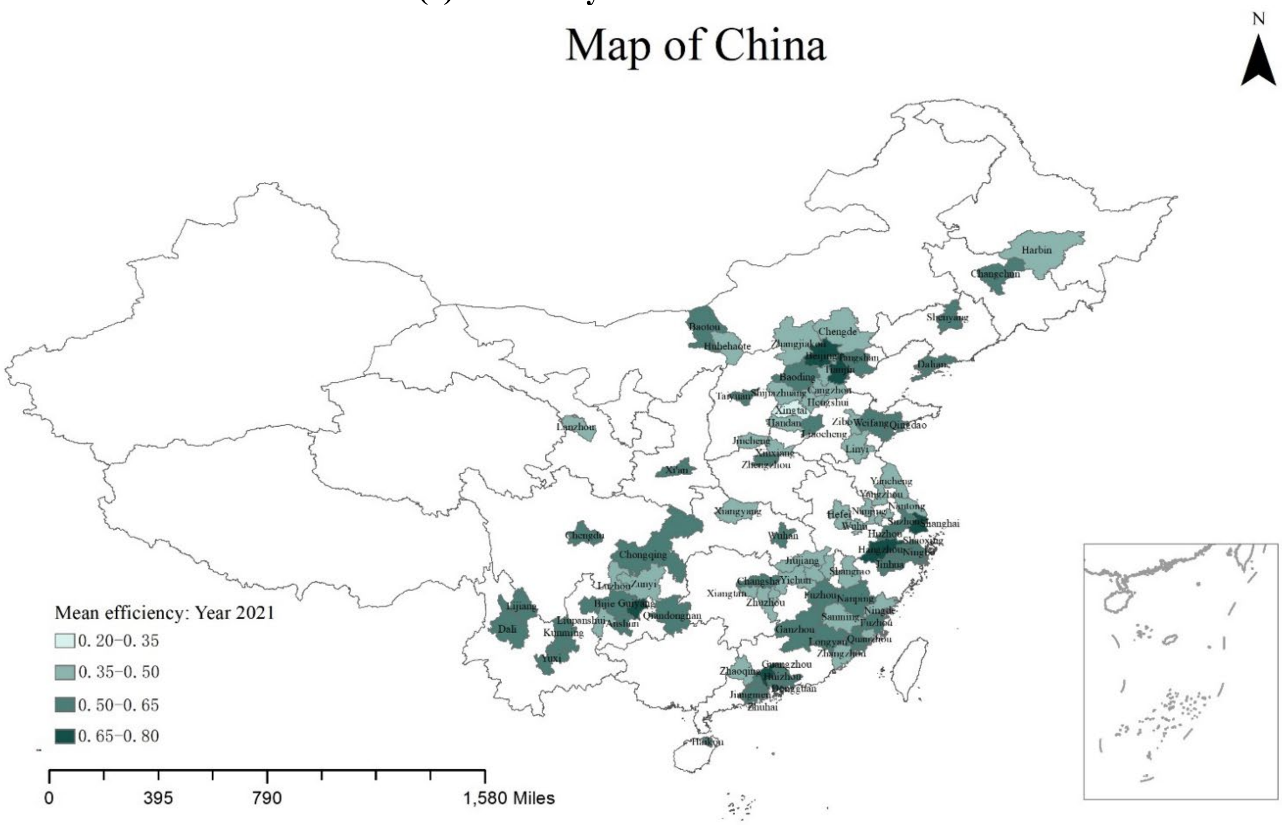
The estimated model parameters embedded within the technical inefficient component of the A-SF are of particular interest for this study. As seen from the table, the introduction of driving and purchase restrictions on conventional vehicles contributes to diminish the inefficiency of the EV market in the 88 demonstration cities. In a similar vein, the economic stimuli that local governments have introduced to sustain the construction and operation of public EV chargers 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. Finally, σ_S^2 is found to be statistically significant suggesting that there exists heterogeneity in the EV sales registered across the 88 Chinese cities involved in the pilot project. Likewise, γ parameter is statistically significant and equal to 0.786 (close to one) and thus we can assert that the inefficiency effects are likely to have a strong impact on the analysis of the value of the inputs.

5. MODEL APPLICATION

Figure 2 plots the efficiency outputs for each of the 88 pilot cities based on the AS-SF model for the years 2016 (Figure 2a) and 2021 (Figure 2b). Similar plots for the years 2017 to 2020 are available from the authors upon request. Of the 88 cities analysed as part of this study, for the year 2021, Shenzhen (0.7071) and Hangzhou (0.6991) are the two most efficient cities with respect to EV sales, with Tianjin (0.6946), Guangzhou (0.6938) and Beijing (0.6882) being placed third, fourth and fifth. The least efficient city in terms of EV sales is Pingtan (0.3011) followed by Zingtai (0.3917) and Chengde (0.3942). Between 2016 and 2021, the efficiency of EV sales as measured by the AS-SF model improved for 64 of the 88 cities and declined for 24. Seven of 10 most efficient cities in 2016 remain within the top 10 most efficient cities in 2021. Of those that left the top 10 ranking, Tianjin (0.5917 in 2016 and 0.5169 in 2021) dropped from seventh to 37th rank, whilst Weifang (0.5749 in 2016 and 0.5214 in 2021) went from eighth to 34th position and Jinhua (0.5691 in 2016 and 0.5253 in 2021) dropped from ninth to 30th most efficient city. The most dramatic change in efficiency experienced between 2016 and 2012 however was for the city of Pigntan whose EV sales efficiency decreased from 0.5617 (11th ranked city) to 0.3011 (88th or last ranked city), whilst Changchun improved in terms of EV sales, with estimated efficiency rising from 0.3088 (ranked 85) in 2016 to 0.5665 in 2021 (ranked 12).



(a) Efficiency measures for 2016



(b) **Efficiency measures for 2021**

Figure 2: Efficiency outputs by region for 2016-2021

Figure 3 plots the efficiency measures for each of the 88 cities for the years 2016 to 2021. Also displayed is a line of best fit ($R^2 = 0.8253$) showing a downward trend in the efficiency of EV sales between 2016 and 2018, after which the efficiency of the 88 cities EV sales increases to a level above that observed in 2016. Further the spread of efficiency measures decreases year on year with the standard deviation of measures decreasing from 0.0889 in 2016 to 0.0699 in 2021. As displayed in the plot however, the decrease in spread arises from a decrease in overall EV sales efficiency occurring mostly amongst the top performing cities, suggesting that whilst on average, the 88 cities are becoming more efficient with respect to EV sales, that overall efficiency is converging to the mean, particularly for the better performing cities.

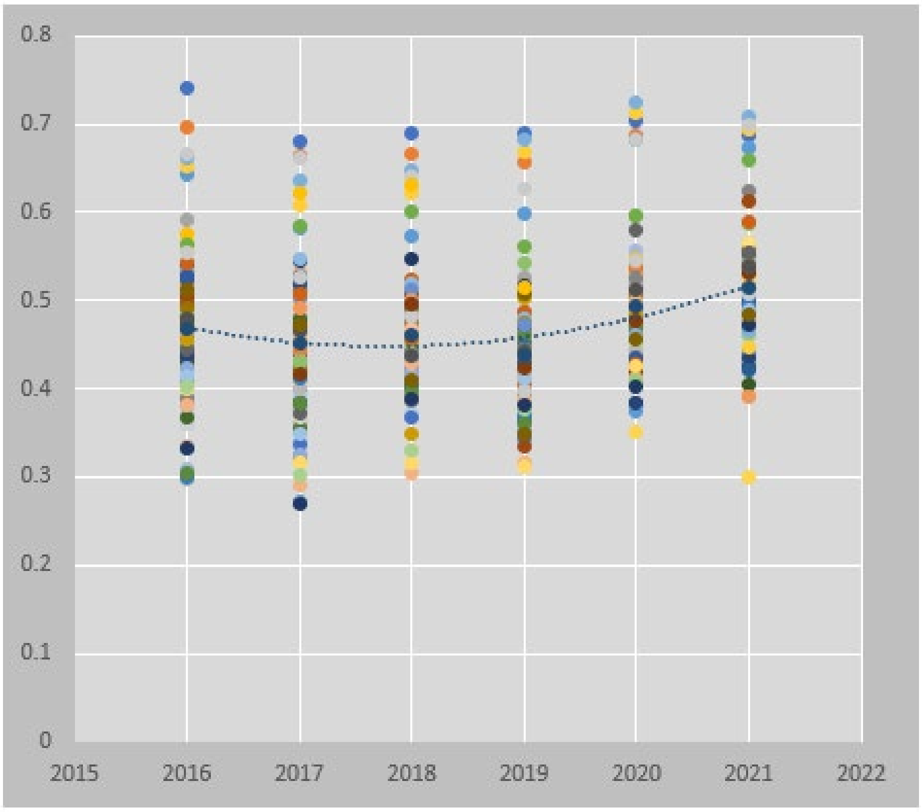


Figure 3: Efficiency Plot 2016-2021

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 six-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 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 grams of CO_2 per km travelled, PHEVs 68 grams 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 7 presents the results using the above approach applying the observed data for each of the 88 cities.

As we can see from Table 7, 2017 represents the worse year in terms of lost potential EV sales (this is also shown in Figure 3), 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 ¥590,864,816.99 (US$85,563,134.15) in tax revenue over the six-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 847,183.43 additional tones of CO2 gases that could have been avoided if the market was operating at the efficient frontier.

Table 7: Base outputs 2016 to 2021*

Year	Lost potential EV sales	(BEV)	(PHEV)	Tax revenue not forgone	Tax revenue not forgone (US$)*	Emissions (tonnes)
2016	4,997.55	3,860.48	1,137.07	¥41,627,380.24	$6,028,060.93	69,068.10
2017	22,779.08	21,119.08	1,660.00	¥235,018,774.79	$34,033,068.78	342,747.62
2018	13,604.46	11,981.98	1,622.48	¥150,149,964.83	$21,743,216.41	199,697.24
2019	6,524.90	6,474.71	50.19	¥66,286,028.18	$9,598,879.74	101,549.72
2020	6,731.51	5,428.79	1,302.72	¥69,494,239.38	$10,063,460.81	94,846.77
2021	2,809.81	2,220.49	589.33	¥28,288,429.57	$4,096,447.49	39,228.97
Total	**57,447.31**	**51,085.52**	**6,361.79**	**¥590,864,816.99**	**$85,563,134.15**	**847,138.43**

* Yuan to US$ exchange rate of 0.14481 as of 7 March 2023

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 8 to 10 respectively. Table 8 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 actually occurred. Indeed, the loss in potential EV sales increases by an average of 1.23 for both BEV and PHEVs, with an additional 13,139.86 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 ¥726,340,003.73 (US$105,181,295.94) 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 1,041,039.16 tonnes over the six-year time frame examined, 193,900.73 over the base scenario.

Table 8: Economic losses 2016 to 2021 assuming 10% tax on petrol*

Year	Lost potential EV sales	(BEV)	(PHEV)	Tax revenue not forgone	Tax revenue not forgone (US$)*	Emissions (tonnes)
2016	6,082.94	4,710.34	1,372.60	¥50,696,317.79	$7,341,333.78	84,159.24
2017	27,832.65	25,806.82	2,025.83	¥287,161,710.92	$41,583,887.36	418,806.05
2018	16,814.42	14,813.18	2,001.25	¥185,561,164.89	$26,871,112.29	246,847.79
2019	8,055.81	7,994.22	61.60	¥82,082,590.20	$11,886,379.89	125,378.86
2020	8,317.27	6,708.30	1,608.97	¥85,916,791.58	$12,441,610.59	117,195.16
2021	3,484.07	2,754.52	729.55	¥34,921,428.36	$5,056,972.04	48,652.06
Total	**70,587.17**	**62,787.38**	**7,799.79**	**¥726,340,003.73**	**$105,181,295.94**	**1,041,039.16**

* Yuan to US$ exchange rate of 0.14481 as of 7 March 2023

Table 9 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 actual observed and predicted sales. With respect to the base scenario, the potential market for EVs over the six years would have been an additional 64,038.27 EVs, 6,590.96 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 therefore earnt the government ¥68,236,466.37 (US$9,881,322.70) in tax receipts that they would have lost had the market for EVs been fully realised. Nevertheless, an additional 944,399.43 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.

Table 9: Economic losses 2016 to 2021 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	5,498.03	4,255.09	1,242.95	¥45,846,879.45	$6,639,086.61	76,048.38
2017	25,298.45	23,463.24	1,835.21	¥261,111,391.41	$37,811,540.59	380,722.05
2018	15,088.89	13,281.59	1,807.30	¥166,597,020.69	$24,124,914.57	221,425.15
2019	7,330.46	7,274.62	55.83	¥74,600,984.62	$10,802,968.58	114,091.28
2020	7,619.27	6,147.29	1,471.99	¥78,597,576.90	$11,381,715.11	107,375.49
2021	3,203.17	2,533.39	669.77	¥32,347,430.30	$4,684,231.38	44,737.09
Total	**64,038.27**	**56,955.21**	**7,083.06**	**¥659,101,283.37**	**$95,444,456.84**	**944,399.43**

* Yuan to US$ exchange rate of 0.14481 as of 7 March 2023

Results from the third and final simulated scenario are given in Table 10. Under the third scenario, the air quality of all 88 cities is assumed to be improved to the highest quality level measured. Under this scenario, the potential number of EV sales falls below the base case over the six years, from 57,447.31 to 51,786.05 EVs, a decrease of 5,661.26 vehicles. The fact that fewer cars are predicted to be sold than for the base scenario results in a decrement in government revenue raised via taxes on ICE vehicles of ¥58,664,006.12 (US$8,495,134.73), dropping from ¥726,340,003.73 (US$105,181,295.94) for the base to ¥659,101,283.37 (US$95,444,456.84) under the scenario being modelled. Finally, emissions are also predicted to be lower than predicted under the base scenario, decreasing from 847,138.43 tonnes of CO2 to 763,501.06 tonnes.

Table 10: Economic losses 2016 to 2021 assuming air quality improves to be below 35 µg/m3for all 88 cities *

Year	Lost potential EV sales	(BEV)	(PHEV)	Tax revenue not forgone	Tax revenue not forgone (US$)*	Emissions (tonnes)
2016	4,436.46	3,427.18	1,009.27	¥36,925,623.42	$5,347,199.53	61,314.65
2017	20,539.32	18,998.31	1,541.01	¥211,937,007.60	$30,690,598.07	308,696.16
2018	12,388.09	10,918.58	1,469.51	¥136,681,854.36	$19,792,899.33	181,905.04
2019	5,870.64	5,823.32	47.32	¥59,269,978.91	$8,582,885.65	91,350.04
2020	6,035.45	4,874.20	1,161.25	¥62,206,689.31	$9,008,150.68	85,092.93
2021	2,516.10	1,990.13	525.97	¥25,179,657.28	$3,646,266.17	35,142.23
Total	**51,786.05**	**46,031.73**	**5,754.32**	**¥532,200,810.88**	**$77,067,999.42**	**763,501.06**

* Yuan to US$ exchange rate of 0.14481 as of 7 March 2023

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 2021. Inputs into the stochastic frontier model include variables associated with whether or not local or central government subsidies were 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 spill over 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. Both direct and spatial effects associated with ICE vehicle sales in previous months are also detected, with a positive overall effect indicated 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, whilst the scale-back structure of purchase subsidies negatively impacts the maximum achievable sales frontier for EVs. On the other hand, local government financial contributions were found to increase the frontier for EV sales whilst summer and low temperatures negatively impact the EV sales frontier. Of some interest is the finding that demand for 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, controls imposed during Covid-19 were found to have mixed effects on EV sales across the 88 cities examined. In general, however, the models explored herein suggest that the market for EV sales was becoming less efficient prior to Covid-19. Nevertheless, since the advent of Covid in 2019, the efficiency of the Chinese EV market has, on average improved, at the cost however of the market regressing to the mean. In particular, our findings suggest that cities found to be less efficient appear to, in the main, have improved substantially, whereas more efficient cities are becoming less efficient over time with respect to converting potential EV sales into actual sales. The fact that the average efficiency level has increased points out that the improvement in less efficient cities over time has outweighed the loss of efficiency for the more efficient markets present within the data.

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, implementing a 10 percent environmental tax on petrol was found to have a larger impact on improving the efficiency of the EV market across the 88 cities, more so than increasing the number of public charging facilities available, or improving the overall air quality experienced within each city. Indeed, as noted earlier, the modelling undertaken suggest 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 Government revenue streams, thus providing somewhat of a disincentive for government to persevere with policies designed to promote EV additional sales. Further, given the finding 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 increase 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 detect 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 2021. Second, unlike previous applications, the data on EV sales span a longer period of time up to 2021 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 prospective 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.

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