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Does smart city policy lead to sustainability of cities?

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ABSTRACT

The popular smart city concept, for some, is viewed as a vision, manifesto or promise aiming to constitute the 21st century's sustainable and ideal city form, while for others it is just a hype. This paper places smart city practices from the UK under the microscope to investigate their contributions in achieving sustainable urban outcomes. Panel data analysis methods were employed to investigate changes in carbon dioxide emissions level of 15 UK cities with differential level of city smartness over the period of 2005–2013. The findings reveal that the link between city smartness and carbon dioxide emissions is not linear, and the impact of city smartness on carbon dioxide emissions does not change over time. This finding calls for better aligning smart city strategies to lead to concrete sustainable outcomes. The paper concludes by highlighting the importance of prospective investigations to accurately scrutinise existing smart city projects' outcomes, and emphasising the necessity of developing smart city agendas that deliver sustainable outcomes.

1. Introduction

Not to a surprise, the 21st century is promoted as the 'century of cities' (Carrillo et al., 2014). By 2030, 60% of the world's population is expected to live in mega-cities; by 2050, 75% of the world's population will be living in urban areas; and this figure will reach to over 80% at the end of the century (Hardoy et al., 2013; Dizdaroglu and Yigitcanlar, 2014). Today, some of the developed nations have already exceeded this urbanisation rate. For instance, in the UK well over 80% of the population is residing in urban areas. Moreover, the Anthropocene era is already upon us, which is characterised by massive human impacts on geological and ecological systems (Crutzen and Steffen, 2003).

Urban growth is a major phenomenon of the Anthropocene era, which is taking place on an unprecedented scale globally, and its impacts on society and the environment are evident (Perveen et al., 2017). Particularly, greenhouse gas (GHG) emissions, including carbon dioxide (CO_2), are major contributors of the global warming (Mahbub et al., 2011; Yigitcanlar and Dizdaroglu, 2015). Climate change in this era has severe implications for the security of individuals, communities, cities, regions, and the planet (Deilami et al., 2018). Mitigating global climate change and neutralising the impacts of fossil fuel-based energy policy on the environment have emerged as the biggest challenges for the planet, threatening both natural and built systems with long-term consequences (Dur and Yigitcanlar, 2015; Arbolino et al., 2017). In recent years, a broad consensus is established on sustainable urban development—or smart growth—being a panacea to the ills of the Anthropocene era—such as the Paris Agreement (Dizdaroglu et al., 2012; Yigitcanlar and Kamruzzaman, 2014). Consequently, the challenge of sustainable urban development has resulted in 'smart cities' and appeared as a hot topic of research and practice globally.

Over the past decade smart urban technologies, as part of the smart city agenda, have begun to blanket our cities with an aim of forming the backbone of a large and intelligent infrastructure (Lee et al., 2008). Along with this development, dissemination of the sustainability ideology has had a significant imprint on the planning and development of our cities (Zhao, 2011; Goonetilleke et al., 2014). Today, the smart city concept is viewed as a vision, manifesto or promise aiming to constitute the 21st century's sustainable and ideal city form. In other words, smart city is an efficient, technologically advanced, green and socially inclusive city (Vanolo, 2014). This is to say, smart city applications place a particular technology focus at the forefront of generating solutions for ecological, societal, economic, and management challenges (Yigitcanlar, 2016). However, despite their promise to deliver sustainable outcomes with the aid of advanced technology, smart cities are heavily criticised as being just a buzz phrase that has outlived their usefulness (Kunzmann, 2014; Shelton et al., 2015).

Smart cities' primary focus mostly being exclusive to technology has been heavily criticised by a number of scholars. For instance, the darker side of smart cities—particularly the extreme dependency on technology, and on corporations dominating technology and related services—is mentioned in the literature as threatening. As stated by Kunzmann (2014, p. 17), "sooner or later society will not manage any more to live without the ICT-based services. Like addicts, or chronically sick patients who are extremely suffering from the lack of some

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substance, respectively the medicine they are relying on, citizens will become sick, if the access to smart ICT services will be cut-off. They will soon forget how to survive in cities, once smart ICT technologies are not available any more. The concentration processes, which characterize the global market of smart technologies, are threatening".

Smart city projects are big and expensive investments that are supposed to drive societal and environmental transformations. However, for example after more than a decade of investment, Songdo City (Korea)—widely referred to as the world's first smart city—is still a 'work in progress' project without concrete sustainable outcomes (Yigitcanlar and Lee, 2014). On the contrary, Shwayri (2013) pinpoints the negative environmental externalities caused by the development of the Songdo smart city.

In spite of the heavy criticisms of smart city sceptics of this type of urban form and development practice, as presented above, there is a general sense among the scholars that rethinking our cities' planning and development paradigms and processes in the age of digital disruption and climate change is a good thing (Angelidou, 2017). It is, thus, imperative to clearly understand what smart city agenda can deliver for cities before our governments are heavily investing on, and jumping on to the smart city bandwagon. However, despite the increasing popularity of the paradigms of smart and sustainable cities, measuring sustainability levels of smart cities is an under-investigated research area. Moreover, there are no empirical studies, so far, scrutinising the GHG emissions of so-called smart cities—the literature mainly focuses on the sustainable city context rather than smart cities (Coutts et al., 2010; Velasco and Roth, 2010).

Against this backdrop, the study aims to capture the big picture view on whether smart city practices have been making considerable contributions to local sustainability agendas by improving sustainable urban development outcomes. Empirically investigating sustainability achievements of smart cities is important to provide evidence on whether this new and popular smart city policy contributes to the sustainability agendas and/or accomplishments of cities. As both smart cites and sustainable urban development concepts are highly complex in nature, for practical reasons, the paper uses proxies for these concepts: (a) Smart cities concept is characterised as city smartness, and; (b) Sustainable urban development concept is characterised as CO_2 emissions. In order to address the critical issue of whether smart city policy leads to sustainability of cities, the paper focuses on the following two research questions:

(a) Does city smartness bring sustainability to cities in terms of CO_2 emissions?
(b) Does the impact of city smartness on CO_2 emissions change over time?

Following this introduction in Section 1 of the paper, Section 2 provides a review of the literature on smart city concepts, and their potential links with urban sustainability. Next, Section 3 outlines the data and methods applied to address the research questions. Afterwards, the findings of the empirical analysis are presented in Section 4, and discussed in policy terms. Finally, Section 5 concludes this paper by highlighting the key findings of the study.

2. Literature review

The adoption of technology is a global phenomenon, and the intensity of its usage is impressive all over the world. Particularly, state-of-the-art smart urban information technologies play critical roles in supporting decision-making, design, planning, development, and management operations of complex urban environments (Yigitcanlar, 2015). Their role in dealing with complexity and uncertainty and in generating sustainable and liveable urban environments has been a popular subject for many scholars (Lee et al., 2014). This has brought, with strong push from major global technology companies—such as IBM, Cisco, Schneider Electric, Siemens, Oracle—, the smart city notion and practice to the forefront of urban agenda in many cities of the world (Alizadeh, 2017).

As stated by Goh (2015, p. 169), "visions of a kind of technology-infused smart city are becoming reality, translated from the realm of concepts into actual urban space". Particularly the development of smart urban systems through effective use of smart urban technologies is providing an invaluable foundation for smart cities to surface. Today, more and more governments are showing interest in smart urban system investment to make cities more efficient, sustainable and inclusive. Consequently, it is estimated that the global market for smart urban systems for transport, energy, healthcare, water and waste will be around US$400 billion per annum by 2020 (Yigitcanlar, 2016). This is to say smart urban systems will fast become an integral part of our lives. In recent years, many researchers explored the most common and advanced smart urban systems, and offered examples of their adoption in the contemporary cities of the world (Klauser and Albrechtslund, 2014).

Over the past decade smart urban technologies have started to form the backbone of a large and intelligent infrastructure network in cities. Along with this development, dissemination of the sustainability ideology has had a significant imprint on the planning, development and management of our cities (Dizdaroglu and Yigitcanlar, 2016). Accordingly, the concept of smart cities, evolved from intelligent cities (Komninos, 2008), has become a popular topic particularly for scholars, urban planners, urban administrations, urban development and real estate companies, and corporate technology firms.

Despite its popularity, so far, there is no prevalent or universally acknowledged definition of smart cities. Instead, there are numerous perspectives on what constitute a smart city. These are ranging from purely ecological (Lim and Liu, 2010) to technological (Townsend, 2013), and from economic (Kourtit et al., 2012) to organisational (Hollands, 2015), and societal (Deakin and Al Waer, 2012) views. Ecological perspective of smart cities focuses on getting local governments, businesses and communities to commit to reducing GHG emissions, reversing sprawling development, increasing urban density, increasing greenspaces, encouraging polycentric development, and so on (Lazaroiu and Roscia, 2012). Technological perspective focuses on adoption of smart urban technology solutions to improve liveability of communities and sustainability of cities—these technologies also include infrastructural ICTs that serves as the backbone such as internet and world wide web (Paroutis et al., 2014). Economic perspective focuses on generating an innovation economy through smart technology solution development, thus increasing the GDP and self-containment of the city (Zygiaris, 2013). Organisational perspective focuses on establishing a transparent and democratic governance model (Meijer and Bolívar, 2016). Societal perspective focuses on establishing socio-economic equality and public participation in the smart city planning and initiatives (Lara et al., 2016).

As for Kitchin (2015), smart city symbolises a new kind of technology-led urban utopia. Utopia or not, in all above mentioned perspectives the vision of technology and innovation is a common ground to shape our cities into a form that we want to leave to our descendants. This is to say, without a commonly agreed definition, the smart cities concept is broadly viewed as a vision, manifesto or provocation—encompassing techno-economic, techno-societal, techno-spatial, and techno-organisational dimensions—aiming to constitute the sustainable and ideal 21 st century city form (Yigitcanlar, 2016). Nevertheless, presently, there are no fully-fledged smart cities (Trindade et al., 2017).

Stated by Glasmeier and Christopherson (2015, p. 4), "over 26 global cities are expected to be smart cities in 2025, with more than 50% of these smart cities from Europe and North America". Smart cities are a global phenomenon today, as there are well over 250 smart city projects underway across 178 cities around the world. The potential success of these cities triggers much more cities to follow their footsteps—for instance, announced in 2015 the Smart Cities Mission of India targets the development of 100 smart cities (Praharaj et al., 2017).

At the moment with the building or retrofitting of many of these cities underway in a large number of places around the world, smart city examples abound in both the popular media and in academic discussions. Nevertheless, in a recent study, Alizadeh (2017) highlights the limited empirical evidence—on whether these cities will be able to keep up to their promises in forming green and inclusive urban environments—as the major shortcoming of the smart cities agenda. She raises concerns on the unjustified popularity of the concept, as there is "limited number of in-depth empirical case studies of smart city initiatives… lack of holistic studies that compare smart city developments in different locales… and limited collaborative engagement with various stakeholders in smart cities studies (p.71)".

In spite of many cities being claimed as smart cities or at least having declared themselves that they are smart, for some scholars, the current hype around smart cities tends to be mostly technocratic, and beyond speculation. There is no strong evidence to suggest that a smart city can provide genuine answers to a number of complex problems cities face today (Anthopoulos, 2017). As underlined by Mora et al. (2017, p. 20), "the knowledge necessary to understand the process of building effective smart cities in the real-world has not yet been produced, nor the tools for supporting the actors involved in this activity".

This issue brings the crucial need for further empirical studies on smart city strategies and initiatives, and forms the rationale of this study. Popularity and relatively widespread application of smart city initiatives provide us the ability to place these cities—even they are not developed as a fully functioning smart cities—under the microscope to evaluate their performance in achieving sustainable urban outcomes.

3. Data and methods

3.1. Data

This research was conducted in the context of smart cities in the UK to answer the research questions. The selection of the UK as the study context is justified as: (a) Being one of the early adopter nations of the smart cities concept and practices (Caragliu et al., 2011); (b) Having the second highest city numbers (7), after the USA (9), within the top-100 smart cities of the world (IESE, 2016), and; (c) Having the highest number of projects (28/148) listed in the top smart city projects of the world (Nominet, 2016). This research utilised a number of secondary sources to gather and analyse data—to address the research questions mentioned earlier—as outlined below.

3.1.1. CO2 emissions data

The CO_2 emissions data were obtained from the Centre for Cities website (http://www.centreforcities.org/data-tool/su/f5fb2e6f). The website reported per capita CO_2 emissions level (tons) of 65 UK cities from 2005 to 2014. The CO_2 emissions data were originally sourced from the UK Department of Energy and Climate Change. CO_2 emissions data were used as an outcome variable in this research and regressed by city smartness data to identify their cross-sectional and temporal impacts.

3.1.2. City smartness data

Some studies try to understand city smartness by considering a set of variables inside the urban system (Fistola and La Rocca, 2014). The business vision of a smart city is strongly based on the pivotal role of technology, especially the ICT (Dameri and Rosenthal-Sabroux, 2014). IESE (2016) highlights that ICT is part of the backbone of any society that wants to be called 'smart'. As a result, this research used two indicators of city smartness representing the ICT penetration in cities: (a) Number of websites hosted per 1000 population, and; (b) Internet protocol (IP) addresses per 1000 population. The number of websites hosted by a city indicates the quality of online services provided by the city, showing support for ICT dissemination strategies. IP address is a unique identifier assigned to each computer and other devices (e.g., mobile phone) connected to the internet. This is a commercial indicator of the adoption of the internet by the public in a city (IESE, 2016). These two datasets were obtained from the MYIP website (https://myip.ms/browse/cities/IP_Addresses_Cities.html). They represented the snapshots of the indicators in a point in time (year 2017). This research derived a quartile classification of the data for a consistent comparison among the cities over time, given that this is a real-time data and susceptible to change over time, albeit slowly.

3.1.3. Urban form characteristics

Four variables representing the urban form characteristics were obtained from the OECD websites (https://data.oecd.org). These included: (a) Population density of cities (person/km^2); (b) Green area (m^2 per million person)—defined as the land in metropolitan areas covered by vegetation, croplands, forests, shrubs lands, and grasslands; (c) Polycentricity—the number of city cores included in a metropolitan area, and; (d) Urban sprawl index (SI)—measures the evolution of sprawl over time in a metropolitan area, based on Eq. (1) (OECD, 2016).

$$SI_i = \frac{\left[urb_{i,t+n} - \left(urb_{i,t}*\left(\frac{pop_{i,t+n}}{pop_{i,t}}\right)\right)\right]}{urb_{i,t}}*100 \quad (1)$$

where, i refers to a particular metropolitan area, t refers to the initial year, $t + n$ refers to the final year, urb refers to the built-up area in km^2, and pop refers to the total population.

The SI measures the growth in built-up area adjusted for the growth in city population. When the city population changes, the index measures the increase in the built-up area relative to a benchmark where the built-up area would have increased in line with population growth. The SI index is equal to zero when both population and built-up area are stable over time. It is bigger (or lower) than zero when the growth of built-up area is greater (or smaller) than the growth of population, i.e., the city density has decreased (or increased).

Note that the SI data were available only for the period of 2006 whereas datasets for the remaining three variables were available from 2000 to 2013 during the preparation of this manuscript. However, an initial investigation shows that the level of polycentricity has not changed over the period meaning that this variable is also static in nature. In addition, a cross-examination between the CO_2 emissions dataset and urban form dataset shows that only 15 metropolitan areas are common in both datasets. As a result, the analysis presented in this paper is restricted to 15 UK cities—i.e., Birmingham, Bradford, Bristol, Cardiff, Edinburgh, Glasgow, Leeds, Leicester, Liverpool, London, Manchester, Newcastle, Nottingham, Portsmouth, and Sheffield—with panel data spanning from 2005 to 2013.

3.1.4. Socioeconomic data

Many prior studies have found linear relationships between per capita CO_2 emissions and per capita GDP (Du et al., 2012; Yang et al., 2015). This paper used per capita GDP (US$, constant prices in 2010) to represent the level of socioeconomic development of the selected 15 metropolitan areas.

3.1.5. Descriptive summary

Table 1 shows descriptive statistics of the data used in this research. Given the panel nature of the variables, the summary table presents three types of variations in data (overall, between the 15 cities, and within a city over the nine years study period). The first variable is individual city ID (identification), which is not a real variable but shows the cross-sectional dimension of the data. It varies from 1 to 15—i.e., the total number of cities (observation) analysed. The next variable is

Table 1
Summary statistics of the variables.

Variable Name	Description	Summary	Mean	Std. Dev.	Min	Max	Observations
ID	ID of the case study cities	overall			1	15	N = 135
		between			1	15	n = 15
		within			8	8	T = 9
Year	Observation year	overall			2005	2013	N = 135
		between			2009	2009	n = 15
		within			2005	2013	T = 9
CO_2	Per capita CO_2 emissions (tons)	overall	6.36	0.79	4.79	8.4	N = 135
		between		0.51	5.42	7.03	n = 15
		within		0.62	5.26	7.79	T = 9
Websites	Quartile classification of the number of website hosted per 1000 population	overall	2.6	1.09	1	4	N = 135
		between		1.12	1	4	n = 15
		within		0	2.6	2.6	T = 9
IP address	Quartile classification of the number of IP addresses per 1000 population	overall	2.6	1.09	1	4	N = 135
		between		1.12	1	4	n = 15
		within		0	2.6	2.6	T = 9
GDP	Per capita GDP (US$, 2010)	overall	35986.9	7328.8	24949.1	54537.86	N = 135
		between		7478.48	26762.7	53284.92	n = 15
		within		1059.75	33825.3	38616.93	T = 9
Green	Green area (m^2 per million person)	overall	163.28	76.57	35.61	329.70	N = 135
		between		78.83	37.42	315.67	n = 15
		within		4.36	149.18	177.32	T = 9
Density	Population density (person/km^2)	overall	2301.06	868.57	894.85	4011.50	N = 135
		between		893.14	923.47	3815.93	n = 15
		within		65.81	2118.69	2496.63	T = 9
Sprawl	Sprawl index (SI)	overall	−2.82	2.04	−6.78	0.62	N = 135
		between		2.10	−6.78	0.62	n = 15
		within		0	−2.82	−2.82	T = 9
Polycentricity	Number of functional centres	overall	1.6	1.26	1	6	N = 135
		between		1.30	1	6	n = 15
		within		0	1.6	1.6	T = 9

the time dimension of the data (year) and varies from 2005 to 2013 (nine years of data). These two variables are used to classify the panel nature of the data.

The CO_2 emissions variable is the main outcome variable used in this research (Kamruzzaman et al., 2015). The mean value of the CO_2 emissions data is 6.36 tons, which means that on average each person emitted 6.36 tons of CO_2 in a year. The overall standard deviation of this variable is 0.79 tons with between and within variations are respectively 0.51 tons and 0.62 tons. This means that there is a greater variation in the emissions levels over the periods within a city than between cities.

The research used two key exposure variables: (a) Number of websites hosted per 1000 population by the cities, and; (b) Number of IP addresses per 1000 population. These are classified as quartiles, and as a result, the overall variation is shown between 1 (lowest quartile) and 4 (highest quartile). Note that the within variations in these datasets are 0 (zero), which means that these variables are time-invariant—that is the classification of the cities does not change over time. This rule applies to the two urban form variables (polycentricity, and SI) because they are time-invariant as well (measured only once). In contrast to the CO_2 emissions variables, GDP, green area, and population density variables have a larger variation between the cities than within a city over time.

3.2. Methods

As for the statistical investigation, a panel data analysis is conducted to observe sustainability related performance figures (e.g., CO_2 emission levels) from pre-introduction (year 2005) of the smart city policy to post-policy period (year 2013) of the selected UK cities. The panel dataset consists of both cross-sectional and time series dimension, which are required to analyse the differences between cities and changes within cities over time. The dependent variable (CO_2 emissions) as used in this research is continuous in nature and varies over time (time-varying variable). The independent variables consist of both categorical (website, and IP address) and continuous data types (GDP, population density, green area, polycentricity, and SI). Some of the independent variables vary over time (time-varying: GDP, population density, and green area) whereas the remaining independent variables are time-invariant. These complexities, particularly with the nature of the main outcome variable (CO_2 emissions) and exposure variables (website, and IP address), possess unique challenges in this research to estimate a panel data model in order to answer the research questions. This research overcomes the challenges by estimating three models as outlined below.

3.2.1. Pooled regression model

A first step in the analysis of the data was to pool the information from all $t = 1,\ldots, 9$ panel waves for all $i = 1,\ldots, 15$ cities and treated them as though they represented independent information for n = 9 * 15 = 135 cities. An ordinary least square (OLS) regression model was estimated (Eq. (2)) using these pool dataset, assuming that the residual (ε_{it}) behaves like the OLS error term.

$$y_{it} = \beta_0 + \beta_1 x_{1it} + \ldots + \beta_k x_{kit} + \gamma_1 z_{1i} + \ldots + \gamma_j z_{ji} + \varepsilon_{it} \tag{2}$$

where, subscript i refers to the $i = 1,\ldots, 15$ cities, which have been observed at $t = 1,\ldots, 9$ equidistant points in time; y_{it} denotes the value of the dependent variable CO_2 emissions for city i at time point t; k and j represent time-variant ($\beta_1 x_{1it} \ldots \beta_k x_{kit}$) and time-invariant ($\gamma_1 z_{1i} \ldots \gamma_1 z_{ji}$) independent variables; and $\beta_1 \ldots \beta_k$ and $\gamma_1 \ldots \gamma_j$ denote the corresponding regression coefficients to be estimated.

Previous studies have derived a logarithmic transformation of the CO_2 emissions data prior to conducting regression analysis (Du et al., 2012; Yang et al., 2015). Our analysis shows that the outcome variable is approximately normally distributed and a natural log transformation did not improve the distribution (Fig. 1). As a result, we have used the observed CO_2 emissions score in all analyses presented in this research.

OLS is applicable to cross-sectional data if certain assumptions are met, particularly with the assumption of no serial correlation in the outcome variable. With panel data, this is at stake. Three causes of

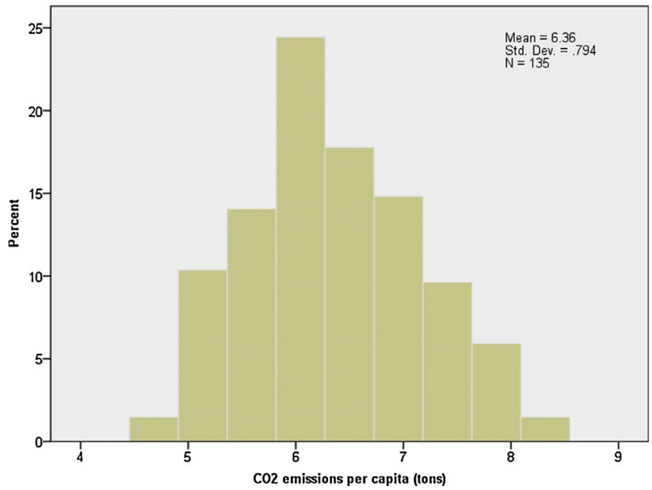

Fig. 1. Distribution of CO_2 emissions.

serial correlation of the dependent variable are: (a) Time-constant explanatory variables that cause Y to be persistently above (or below) the average; (b) Serially correlated time-varying explanatory variables, and; (c) True state dependence of the dependent variable itself (Andreß, 2013). In relation to the first cause, the sustainability vision of a city, for instance, is a typical example of a theoretically important, but hard-to-measure explanatory factor. Different cities have different sustainability agendas, which cannot be measured and controlled in the model. If they are constant over time, this unobserved heterogeneity causes some cities to have disproportionately higher (or lower) CO_2 emissions in all years than could be expected from the independent variables in the model. Pooled OLS is only unbiased, if we are ready to assume that this unobserved heterogeneity (e.g., differences with respect to sustainability vision) is independent of the explanatory variables in the model. In addition, if there is unobserved unit-specific heterogeneity that is constant over time, and even when it is uncorrelated with the variables in the model, error terms at different time points could be correlated with one another. Taking the panel structure of the dataset into account is a possible way forward to address these problems.

3.2.2. Two-way fixed effect panel data model

Apparently, pooled OLS makes unrealistic assumptions about panel data. However, the model is easily extended to account for unobserved heterogeneity at the unit level. The stochastic part of the model (ε_{it}), as presented in Eq. (2), can be distinguished between two components ($\varepsilon_{it} = \mu_i + e_{it}$): (a) μ_i: unobserved predictors of Y that are specific to the unit and therefore time-constant, and; (b) e_{it}: unobserved predictors of Y that are specific to the time point and the unit (including measurement errors). Again, depending on our assumptions about these two error terms, different estimation procedures are available. A simple starting point is the assumption that the time-varying error, e_{it}, has the same properties as the error term in OLS estimation. In other words, e_{it} is assumed to be purely random 'white noise'—idiosyncratic error. Yet, the main discussion revolves around the unit-specific error, μ_i. Fixed effect (FE) model assumes that something within the city may impact or bias the predictor or outcome variables and we need to control for this. This is the rationale behind the assumption of the correlation between unit-specific error, μ_i and predictor variables. FE removes the effect of those time-invariant characteristics so we can assess the net effect of the predictors on the outcome variable. Another important assumption of the FE model is that those time-invariant characteristics are unique to the cities and should not be correlated with other city characteristics. Each city is different, and therefore, the city's error term and the constant, which captures cities characteristics, should not be correlated with the others.

In order to account for individual fixed effects and time period fixed effects simultaneously, we constructed a two-way fixed effect model based on a generic panel data model. Additionally, FE regression—by definition—is not the technique to estimate the effects of time-constant explanatory variables Z. It should be stressed, however, that FE regression controls for all (observed and unobserved) time-constant determinants of Y, even if it does not provide with numerical estimates of their effects. However, this goes against our research question to be answered: how time-constant city smartness factors influence CO_2 emissions over time. In order to overcome this limitation, we have extended the analysis by including interactions with time. Since 'year' variable has nine categories, there are eight interactions with each predictor. Note that the other time-invariant predictors (e.g., polycentricity) do not have main effects included in the model. If we had tried to include them, the software would have dropped them from the model because they have no variation within cities (unless they are also interacted with time). Our estimation function is (α_i is the city specific effect that captures all observed and unobserved heterogeneity of cities) in Eq. (3):

$$y_{it} = \beta_0 + \beta_t.\ t + \beta_1 IP_i.\ t + \beta_2 Web_i.\ t + \beta_3 GDP_{it} + \beta_4 Green_{it} + \beta_5 Density_{it} + \alpha_i + \varepsilon_{it} \quad (3)$$

3.2.3. Random effect panel data model

The fixed-effects model controls for all time-invariant differences between the cities, so the estimated coefficients of the fixed-effects models cannot be biased because of omitted time-invariant characteristics such as city vision, culture. One side effect of the FE models is that they cannot be used to investigate time-invariant causes of the dependent variables. Technically, $\alpha_i$time-invariant characteristics of the cities are perfectly collinear with the city dummies, α_i Substantively, fixed-effects models are designed to study the causes of changes within a city. A time-invariant characteristic cannot cause such a change, because it is constant for each city.

The rationale behind random effects (RE) model is that, unlike the fixed effects model, the variation across cities is assumed to be random and uncorrelated with the predictor or independent variables included in the model. Researchers have suggested that if there is a reason to believe that differences across entities have some influence on dependent variable, then one should use random effects (Baltagi, 2008). An advantage of random effects is that time invariant variables (i.e., polycentricity) can be included in the model. In the fixed effects model these variables are absorbed by the intercept.

The RE model is based on the same equation that we used for the fixed effect model but including the time-constant independent variables. The crucial difference between FE and RE is that now, instead of treating α_i as a set of fixed numbers, we assume that α_i is a set of random variables with a specified probability distribution. For example, it is typical to assume that each α_i is normally distributed with a mean of 0, constant variance, and is independent of all the other variables on the right-hand side of the equation. The most apparent difference between the fixed and the random effects models is that the random effects method can include time-invariant predictors.

3.2.4. Choosing between RE and FE models

In this research, we performed the Hausman test to select the appropriate model between FE and RE models, and the result indicated that the fixed-effects model was better than the random-effects model (chi-square = 19.56, p-value = 0.0337). However, given the requirements to answer the research questions, it is imperative to analyse the effect of time-constant variables Z on the dependent variable Y, and as a result, we have decided to present results from all three models in this research. All tests were run in Stata 13.1.

3.2.5. Testing for time-fixed effects

We have conducted additional test (*testparm* command in Stata) to see if time fixed effects are needed when running the two-way FE

Table 2
Classification of case study cities according to their smartness status.

Case study cities	Quartile classification of city smartness based on:		IESW rank[a]	Huawei rank[b]
	IP address	Websites hosted		
Birmingham	2nd	3rd	118	3
Bradford	2nd	1st	–	
Bristol	4th	4th	–	2
Cardiff	1st	1st	–	
Edinburgh	4th	3rd	–	
Glasgow	4th	2nd	49	4
Leeds	2nd	2nd	156	7
Leicester	3rd	1st	–	
Liverpool	4th	4th	93	
London	2nd	4th	3	1
Manchester	3rd	4th	145	5
Newcastle	1st	3rd	–	
Nottingham	3rd	3rd	178	9
Portsmouth	1st	2nd	–	
Sheffield	3rd	2nd	–	10

[a] Ranking among the world cities based on technology dimension, lower rank corresponds to higher smartness.
[b] Ranking among the UK cities, lower rank corresponds to higher smartness.

model. It is a joint test to see if the dummies for all years are equal to 0. If they are 0, then no time fixed effects are needed. A statistically significant test result was found (F = 8.56, p-value = 0.000) suggesting that an inclusion of the time dummies was better than their omission from the model.

4. Results and discussion

4.1. City smartness and CO_2 emissions: descriptive findings

The findings of the analysis (Table 2) suggest that: (a) Some cities consistently maintained their ranking in both indicators (i.e., Bristol, Cardiff, Leeds, Liverpool, Nottingham); (b) The ranking has changed for the remaining cities justifying the need to investigate for both city smartness indicators, and; (c) The use of these indicators have also been justified because external city smartness or smart city rankings seem to correspond with our ranking. For example, Bristol has been ranked 2nd among the UK cities based on the Huawei rank. Our ranking has also consistently identified Bristol in the upper quartile.

Fig. 2a shows the average per capita CO_2 emissions from 2005 to 2013 according to the IP address classification. From Fig. 2a, we find that per capita CO_2 emissions gradually declined from 2005 irrespective of the classification. The average per capita CO_2 emissions of the cities that fall within the upper quartiles of smartness classification (according to the IP addresses) is remarkably higher than other classes throughout the period. An opposite trend is evident for the cities belong to the second quartile. Cities in the first and third quartile remained in-between these extremes over the period with cities in the third quartile emitting slightly more than the first quartile.

A different trend in the level of CO_2 emissions was observed, when the cities are classified according to the hosted websites (Fig. 2b). In the light of the analysis the key findings include: (a) An overall declining trend—time has an impact on the level of CO_2 emissions, perhaps cities are becoming more aware of sustainability issues and adopting policies and awareness among the city population, and; (b) No clear pattern of the effect of city smartness on CO_2 emissions levels—this needs to be further assessed through regression analysis.

4.2. Estimation results

For each indicator, we present the results for the pooled OLS and panel models (FE and RE) in Table 3. The FE model includes interactions between time and the key exposure variables (IP addresses, and websites hosted) as discussed earlier. We grouped the variables according to broader themes in Table 3 as urban form, socioeconomic, smartness factors, time, and interaction terms. All models were found to be statistically significant with very good explanatory powers (in terms of R^2). Although many of the coefficients appear to be small in the model outputs, these are in fact not small when interpreted. For example, the coefficient of GDP is 0.0001 across the models which looks very small. However, this means that $1 increase in GDP is likely to increase CO_2 emissions by 0.0001 tons (or 0.1 kg).

4.2.1. City smartness and CO_2 emissions

The pooled OLS model shows that all else being equal, cities with more IP addresses (quartiles 3 and 4) are likely to emit a reduced level of CO_2 (Table 3). Findings from the RE model, however, shows that only cities in the third quartile have a statistically significant association. These cities emitted a significantly less amount of CO_2 per capita. In relation to the hosting of websites, the pooled OLS model shows that cities in the third quartile emitted a significantly less CO_2 per capita than cities in the first quartile. However, this is not statistically significant in the RE model although it maintains the direction of association. Unexpectedly, the pooled OLS model shows that cities in the fourth quartile emitted a significantly higher level of CO_2 per capita which remained significant in the RE model. The interaction terms in the FE model were not found to be statistically significant suggesting that the gaps in the CO_2 emissions levels have not been widened (or reduced) significantly between the smartness levels of the cities. That

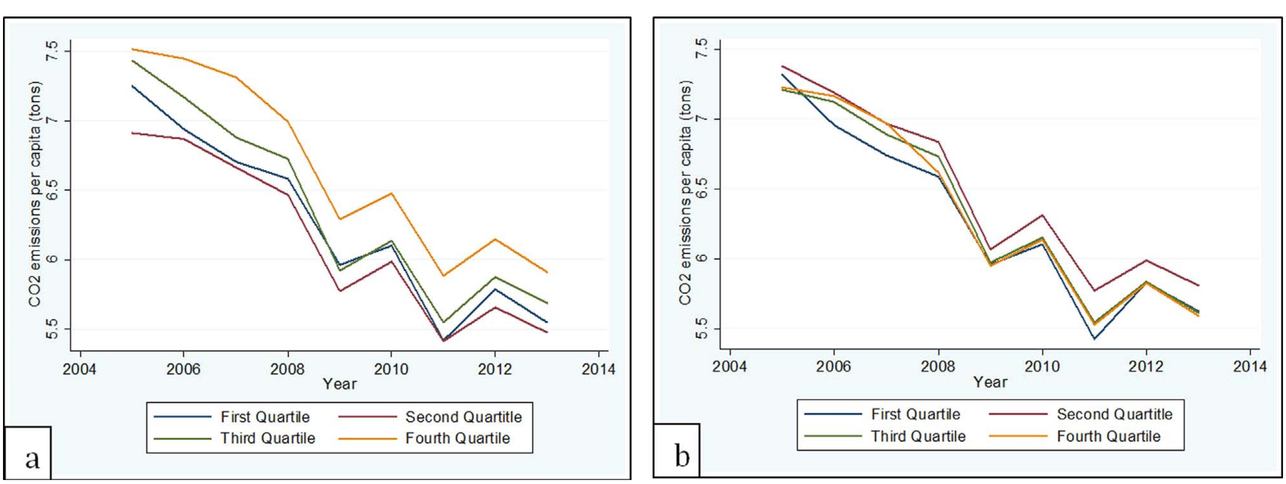

Fig. 2. Per capita CO_2 emissions by city smartness quartiles (a) IP addresses; (b) Websites hosted.

Table 3
Estimation results.

Variables	Pooled OLS model				Fixed effect model			Random effect model		
	Coeff.	t	$P > \lvert t \rvert$	VIF	Coeff.	t	$P > \lvert t \rvert$	Coeff.	z	$P > \lvert z \rvert$
Urban form characteristics										
Population density	0.0004	2.63	0.010	5.16	−0.0020	−3.04	0.003	−0.0002	−0.88	0.381
Green area	0.0136	5.86	0.000	10.80	0.0123	0.85	0.399	0.0101	2.82	0.005
Polycentricity	−0.1403	−1.68	0.095	3.80	Omitted			0.0784	0.55	0.582
Sprawl index	0.3158	5.30	0.000	5.08	Omitted			0.0845	0.88	0.378
Socioeconomic factor										
GDP	0.0001	4.31	0.000	4.16	0.0001	0.64	0.522	0.0001	−0.01	0.992
City smartness factor										
Websites (ref: first)										
Second	−0.0226	−0.10	0.924	3.79	Omitted			0.3849	0.92	0.359
Third	−0.3488	−1.81	0.073	2.52	Omitted			−0.1197	−0.32	0.746
Fourth	0.9961	2.91	0.004	7.97	Omitted			1.2451	2.12	0.034
IP addresses (ref: first)										
Second	0.3458	1.63	0.106	3.06	Omitted			−0.1608	−0.41	0.683
Third	−0.9345	−2.77	0.006	7.70	Omitted			−1.2095	−2.08	0.038
Fourth	−0.8177	−3.24	0.002	4.33	Omitted			0.0828	0.20	0.844
Year (ref: 2005)										
2006					−0.3955	−2.57	0.013	−0.1459	−2.76	0.006
2007					−0.5538	−3.37	0.001	−0.3450	−6.02	0.000
2008					−0.6085	−3.68	0.000	−0.5308	−9.58	0.000
2009					−1.0410	−5.98	0.000	−1.2225	−21.92	0.000
2010					−0.8702	−4.65	0.000	−1.0119	−17.28	0.000
2011					−1.5443	−7.65	0.000	−1.5951	−25.85	0.000
2012					−0.9918	−4.52	0.000	−1.2788	−19.47	0.000
2013					−1.1558	−4.86	0.000	−1.4664	−20.91	0.000
IP address-Year interaction										
Second Quartile#2006					0.2492	1.57	0.121			
Second Quartile#2007					0.2785	1.76	0.084			
Second Quartile#2008					0.2458	1.54	0.128			
Second Quartile#2009					0.1635	1.02	0.311			
Second Quartile#2010					0.2697	1.64	0.106			
Second Quartile#2011					0.3762	2.30	0.025			
Second Quartile#2012					0.2543	1.54	0.129			
Second Quartile#2013					0.3236	1.93	0.058			
Third Quartile#2006					0.0267	0.17	0.868			
Third Quartile#2007					−0.0102	−0.06	0.951			
Third Quartile#2008					0.0115	0.07	0.948			
Third Quartile#2009					−0.1983	−1.07	0.287			
Third Quartile#2010					−0.0998	−0.50	0.620			
Third Quartile#2011					0.0162	0.07	0.941			
Third Quartile#2012					−0.0248	−0.11	0.917			
Third Quartile#2013					0.0445	0.17	0.863			
Fourth Quartile#2006					0.1482	0.87	0.390			
Fourth Quartile#2007					0.2699	1.57	0.122			
Fourth Quartile#2008					0.1466	0.84	0.402			
Fourth Quartile#2009					0.0232	0.13	0.898			
Fourth Quartile#2010					0.1170	0.65	0.520			
Fourth Quartile#2011					0.2029	1.10	0.275			
Fourth Quartile#2012					0.1256	0.66	0.509			
Fourth Quartile#2013					0.1547	0.79	0.432			
Website-Year interaction										
Second Quartile#2006					0.1183	0.74	0.461			
Second Quartile#2007					0.0486	0.30	0.766			
Second Quartile#2008					0.0424	0.25	0.801			
Second Quartile#2009					−0.1277	−0.74	0.463			
Second Quartile#2010					−0.0841	−0.46	0.645			
Second Quartile#2011					0.0189	0.10	0.921			
Second Quartile#2012					−0.2098	−1.06	0.294			
Second Quartile#2013					−0.2185	−1.05	0.298			
Third Quartile#2006					0.2348	1.48	0.144			
Third Quartile#2007					0.1790	1.11	0.271			
Third Quartile#2008					0.1730	1.07	0.289			
Third Quartile#2009					0.0254	0.15	0.878			
Third Quartile#2010					0.0224	0.14	0.893			
Third Quartile#2011					0.0654	0.39	0.699			
Third Quartile#2012					−0.0747	−0.43	0.665			
Third Quartile#2013					−0.1093	−0.62	0.536			
Fourth Quartile#2006					0.2476	1.43	0.157			
Fourth Quartile#2007					0.2062	1.16	0.252			
Fourth Quartile#2008					0.0535	0.29	0.776			

(*continued on next page*)

Table 3 (*continued*)

Variables	Pooled OLS model				Fixed effect model			Random effect model		
	Coeff.	t	P > |t|	VIF	Coeff.	t	P > |t|	Coeff.	z	P > |z|
Fourth Quartile#2009					0.0482	0.24	0.811			
Fourth Quartile#2010					0.0357	0.16	0.870			
Fourth Quartile#2011					0.0946	0.41	0.685			
Fourth Quartile#2012					0.0089	0.04	0.972			
Fourth Quartile#2013					−0.0223	−0.08	0.935			
Constant	2.295969	3.69			8.9833	2.71	0.009	6.0534	7.170	0
N	135				135			135		
F/Chi^2	8.56**		0.000		42.08	0.000		2561.86		0.000
R^2 (Overall)	0.4336				0.09			0.81		
R^2 (Between)					0.03			0.56		
R^2 (Within)					0.98			0.96		

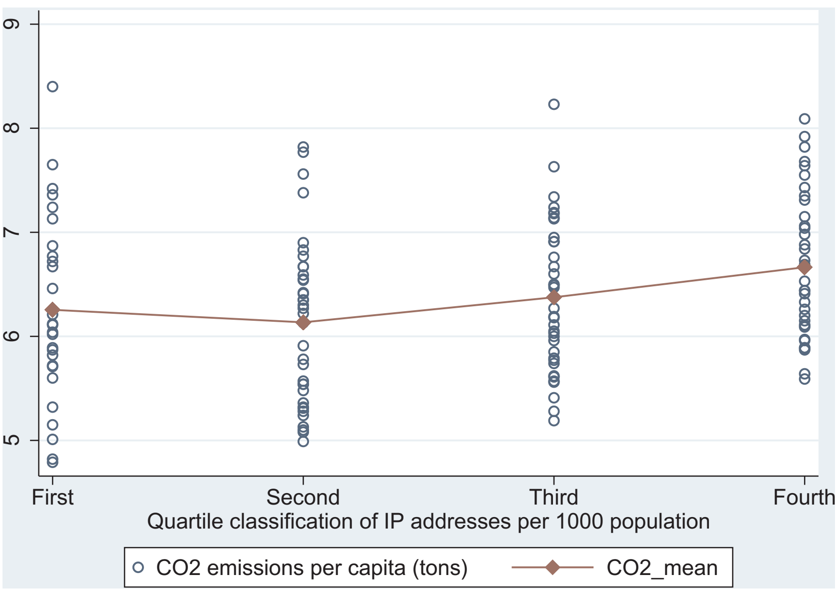

Fig. 3. Heterogeneity in CO_2 emissions according to IP address classification.

means, the cities have been consistent in terms of their efforts of achieving sustainability irrespective of their smartness status. Overall, the findings show that there is a statistically significant relationship between city smartness and CO_2 emissions. However, the relationship is not linear, but tended to be U-shaped (Fig. 3). Overall, there is not temporal effect of the city smartness on CO_2 emissions.

4.2.2. *Urban form and CO_2 emissions*

The pooled OLS model shows that urban population density had positive effect on per capita CO_2 emissions from cities. However, an opposite association was found in the FE and RE models, which show that the relationship is negative—i.e., increasing population density reduces CO_2 emissions. Clearly, the findings from the pooled OLS model are contrary to most studies in the Western countries (Jones and Kammen, 2014). Therefore, the findings from the FE and RE models are more consistent with the previous literature on this topic and justify the application of panel data analytical technique for an unbiased result.

Surprisingly, a positive association between the amount of green area in a city and CO_2 emissions goes against the common wisdom on this topic. Existing knowledge suggests that green area reduces CO_2 emissions (Nowak and Crane, 2002). However, evidence started appearing that green areas emit as much CO_2 as can be found in dense urban area (https://wattsupwiththat.com/2016/02/23/study-urban-backyards-contribute-almost-as-much-co2-as-much-as-cars-and-buildings). The relationship is significant in the pooled OLS model and RE model but not statistically significant in the FE model. It is possible that this variable is correlated with other unobserved variable in the OLS and RE models. The FE model takes into account this unobserved relationship, and as a result, the effect became statistically insignificant. However, we believe that this is an issue that requires much broader discussion and analysis.

Two time-constant urban form variables (SI, and polycentricity) were found to be statistically significant in the OLS model, but not in the RE model. As expected, the pooled OLS model shows that increasing sprawl increases CO_2 emissions level, whereas polycentricity reduces CO_2 emissions levels.

4.2.3. *Socioeconomic effects*

From the estimation results presented in Table 3, per capita GDP had a positive effect on per capita CO_2 emissions in all three models. However, the association is only statistically significant in the pooled OLS model.

4.2.4. *Time effects*

In terms of the effect of time, the annual impact on per capita CO_2 emissions was negative and was highly significant for most years. More importantly, the negative effect increased yearly. This means that per capita CO_2 emissions were reducing over the period and at an increasing rate after controlling for socioeconomic, urban form, and city smartness factors. This suggests that the time period captures factors that were not included in the model—it could be the policy measures that the UK government has undertaken to meet the international obligations such as the Quito protocol.

5. Conclusion

In recent years, the smart cities concept has become an important research topic and a priority policy agenda for many cities from both developed and developing country contexts (Yigitcanlar, 2017). Even smart city technologies are seen crucial for the survival of our species (Townsend, 2013). Today, many of the global cities' administrations view smart urban technology applications and systems as potential vehicles to deal with their current and future developmental challenges whether they are economic, societal or environmental in nature. Consequently, smart cities have become a global phenomenon with over 250 smart city projects underway across 178 cities around the globe.

In many instances, however, the fashionable term smart city is used for branding or marketing purposes with a lack of integrated approach covering sustainability concerns (Söderström et al., 2014; Shelton et al., 2015; Vanolo, 2015). In other words, the fashionable term 'smart' has started to replace 'sustainable' in the brand of many projects—for example, China's Tianjin Eco-City is now also branded as Tianjin Smart City.

According to Ahvenniemi et al. (2017, p.242), "the role of technologies in smart cities should be in enabling sustainable development of cities, not in the new technology as an end in itself. Ultimately, a city that is not sustainable is not really smart". There is little empirical evidence that, despite its promise, smart cities contribute to sustainability agenda of those cities. In order to address this issue of whether smart city really leads to sustainable outcomes, the study at hand has put cities with smart city agendas from the UK under the sustainability performance assessment microscope. Based on the authors' knowledge, this is the first study that attempted to assess a causal relationship between city smartness and sustainability—by using nine waves of panel data.

The findings revealed in this study suggest that, in the investigated cities from the UK context, there is not strong evidence on: (a) A positive correlation between technology adoption and sustainable outcomes, and; (b) The impact of city smartness on CO_2 emissions change over time. In other words, despite to their promise, so far, smart city practices in the UK cities have failed to make a considerable contribution to the sustainability agenda beyond the rhetoric. This finding calls for further investigation and better aligning smart city strategies to lead to concrete sustainable outcomes. In this instance, we would like to highlight the importance of prospective investigations to accurately scrutinise existing smart city projects' outcomes, and emphasising the necessity of developing smart city agendas that deliver sustainability oriented outcomes. This would also help in maturing of the smart city paradigm—as a city planning and development model and emerging urban reality—that is already in continuous transformation.

As underlined by Conroy and Berke (2004), strategically planning our cities, by adopting sustainable urban development principles, is critical to achieve sustainable outcomes—particularly by promoting planning for sustainable urban development at the local level. This in turn helps in generating ecological sustainability that is a critical element of smart cities. In order to achieve comprehensive sustainable urban future outcomes, we also need to focus on the strategic implementation of smart urban technologies rather than the smart cities concept (Taamallah et al., 2017). Moreover, Komninos (2016) highlights that in smart cities there is a need for strategy and leadership, strategic policies and plans that will integrate bottom-up initiatives at company or organisation level with planned projects by various stakeholders under a coherent vision for the future of the ecosystems that make up each city. The critical question here is not about implementing on-the-shelf smart city solutions, but learning to innovate with smart environments, capabilities distributed among organisations, people, machines, and collaborative business models. This approach will better support the success of smart cities movement, and also creating desired sustainable urban futures. This is to say, concepts of smart and sustainable—that are currently not well aligned—need to be brought together through locally designed solutions and strategic planning practices (including strategic implementation of adequate smart urban technologies) for a truly smart and sustainable urban development—hence subsequently leading to the formation of smart and sustainable cities.

In conclusion, this paper generated new insights and empirical evidence on whether smart city policy leads to sustainability of cities—in the case of UK cities—particularly focusing on city smartness and sustainability aspects. However, sustainable urban development is beyond technology and ecology aspects alone; a quadruple bottom line approach is critical—economic, societal, environmental, governance (Yigitcanlar and Teriman, 2015). On this very point Yigitcanlar (2016) suggests that for a successful: (a) *Economic development in smart cities*: We need to give our cities the capability of developing their technologies unique to their own developmental problems and needs. This in turn contributes to the establishment of a local innovation economy and prosperity that is a central element of smart cities; (b) *Sociocultural development in smart cities*: We need to develop our cities wired with smart urban technologies not only exclusive to urban elites, but also inclusive to those unfortunate. This in turn helps in establishing socioeconomic equality that is an essential element of smart cities; (c) *Spatial development in smart cities*: We need to reform our cities by adopting sustainable urban development principles—e.g., minimising urban footprint, limiting GHG emissions, establishing urban farms, and using renewable energy sources. This in turn helps in generating ecological sustainability that is a critical element of smart cities, and; (d) *Institutional development in smart cities*: We need to equip our cities with highly dynamic mechanisms to better plan their growth and manage their day-to-day operational challenges. This in turn helps in performing appropriate strategic planning, development, and management practices that is a coherent vision for the future of urban ecosystems of our smart cities.

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