Air Quality in Smart Sustainable Cities: Target and/or Trigger?

Abstract

Urban areas all over the world are looking to become Smart Sustainable Cities (SSCs), i.e., sustainable urban environments that extensively use ICT and related technologies. However, little is known about the effectiveness of SSC initiatives in terms of sustainable outcomes and/or the factors driving such initiatives. This paper provides empirical evidence on the role of air quality as target of and trigger for SSC initiatives in Wallonian municipalities. Results from regression analyses indicate that, for those municipalities with a higher scope to achieve emissions reductions (low levels of past air quality) and a strong commitment in their smart city initiatives (level of implementation and orientation), SSCs are acting as a successful transnational local initiative for sustainability. They also support the view that sustainability is a major driver of the SSCs, since a better quality of air positively affects the probability that a municipality engages in sustainability-oriented (but also digitally-oriented) smart city initiatives.

Keywords: ICT, smart cities, sustainability, Wallonia

JEL: P25, R11, R58, Q56

1. Introduction

Most people now live in cities, and the trend is growing. According to the *UN 2018 Revision of World Urbanization Prospects*, for example, by 2050 more than two thirds of the world's population will live in cities. The sustainability of these urban areas is therefore critical, even more so when we take into consideration that they are responsible for around three quarters of the CO_2 emissions from global final energy use (*5th Assessment Report by the Intergovernmental Panel on Climate Change of the UN*, ch. 12: 927). A number of global or transnational initiatives, such as the Local Agenda 21 arising from the UN Rio Conference, have attempted to address this sustainability challenge since at least the early 1990s (Zeppel 2013). However, these early global initiatives for the sustainability of cities did not achieve a great deal of success in terms of sustainability outcomes (Krause 2012a, Bansard *et al.* 2017).

In contrast, following on from the Paris Agreement on Climate Change that came into force in 2016, global initiatives for the sustainability of cities seem to have done better (Hawkins *et al.* 2016). Hsu *et al.* (2020: 1016), for example, report that about two thirds of the 1,066 cities that are members of the Covenant of Mayors were close to achieve their emission reduction targets for the year 2020. Also, the 2019 Report of the C40 Cities Climate Leadership Group claims that 53 of their 96 members "have registered five years of emission reductions ('peak emissions'), or are expected to do so by the end of 2020". This is consistent with the findings of Steffen *et al.* (2019) in that members of this network are more likely to have at least one utility-scale solar photovoltaic project than the average mega city (i.e., a city with a population of above 1 million). It is interesting to note, however, that in their logistic regressions Steffen *et al.* (2019) do not find any significant effect of being a member of the other transnational municipal climate networks they consider.

Therefore, extant "evidence on how the climate commitments of cities actually translate into stringent policies and eventually into mitigation outcomes" suggests that commitment and engagement in global sustainability initiatives do not always grant success (Steffen *et al.* 2019: 909). It is consequently important to empirically assess any "additional mitigation opportunities" (Hsu *et al.* 2020: 1021) that may appear at the local level (Hultman *et al.* 2020, Hsu *et al.* 2019). This paper aims to contribute to this literature by analysing the relationship between air quality and "smart city" initiatives (see also Yigitcanlar and Kamruzzaman 2018), i.e., initiatives that seek to achieve the long-term sustainability of the urban environment by making extensive use of Information and Communication Technologies (ICTs; European Commission 2012, Kramers *et al.* 2014, Lee *et al.* 2014).

The global impact of smart city initiatives is illustrated by the fact that more than 700 cities from 150 countries were represented at the recent 2018 Smart City Expo World Congress in Barcelona. Also, according to a recent report by the consulting firm Grand View Research ("Smart Cities Market Size, Share & Trends Analysis Report, 2020-2027") the smart city market amounted to USD 83.9 billion in 2019 and is expected to reach USD 463.9 billion in 2027. In the EU alone, smart city projects over the period 2005 to 2016 had, on average, an estimated cost of nearly €16 million (Collins *et al.* 2017). Yet not all these initiatives and projects are meant to specifically address sustainability issues. In fact, some concentrate mostly on issues involving ICTs and thus follow what can be described as a digital rather than sustainable orientation (Manville *et al.* 2014, Estevez *et al.* 2016, Angelidou 2017). This is therefore a crucial aspect in the development of smart city initiatives that potentially has an important role to play in the pursuit of sustainable goals. However, previous empirical research on the relationship between the smartness of urban areas and their sustainability concentrates on the level of smartness (Yigitcanlar and Kamruzzaman 2018) and does not consider differences arising from sustainable and/or digital orientations.

Similarly, little is known about the drivers of the smart city initiatives that follow a sustainable orientation and whether these are indeed different to those of other smart city orientations (Haarstad 2017, Ahvenniemi *et al.* 2017, Martin *et al.* 2018, Yigitcanlar *et al.* 2019). As de Jong *et al.* (2015) argue, research in this area would not only help to elucidate the concept of the "smart sustainable city" (SSC) but, perhaps more importantly, contribute to our understanding of the expected outcomes and policy implications associated with SSC initiatives. A number of previous studies have looked at the drivers of (trans)national sustainability initiatives developed at the local level (Brody et al. 2008, Zahran *et al.* 2008a, Zahran *et al.* 2008b, Krause 2012a), but none provide evidence on smart city initiatives and/or the differences that may exist if they follow a digital and/or sustainable orientation. The second aim of this paper is to fill this gap by analysing the relationship between sustainability-oriented smart city initiatives and local sustainability conditions, as measured by past air quality (Wang 2012).

In summary, this paper empirically addresses two related research questions on the sustainability of smart cities and its relation to the quality of air in Wallonian municipalities.[1] First, we investigate whether SSC initiatives make a difference in terms of sustainability outcomes and whether they do so regardless of their digital and/or sustainable orientation. In particular, we empirically analyse whether the Wallonian municipalities engaged in smart city initiatives have better levels of air quality and whether this is the case if they follow a sustainable orientation using linear regression models. Second, we investigate whether past sustainability conditions are among the main drivers of the smart city initiatives that follow a sustainable orientation. In particular, we empirically analyse whether past air quality affects the probability that a Wallonian municipality engages in sustainability-oriented smart city initiatives (rather than other smart city orientations) using multinomial logit models.

The rest of the paper is organised as follows. In Section 2 we review the relevant literature. In Section 3 we present the econometric methods and the data employed. In Section 4 we report the main results, and in Section 5 we discuss them in detail. Section 6 concludes.

2. Literature review

This paper is mainly related to two strands of literature. First, studies that analyse the effectiveness of transnational sustainability initiatives developed at the local level. Second, studies that analyse the drivers of such local sustainability initiatives. Next, we discuss these studies with the aim of providing key insights for our empirical strategy, i.e., our empirical strategy is derived from the analysis of the goals, statistical methodology, data and results of these studies. However, since our interest lies in the particular case of the SSCs, it seems necessary to start our literature review with a brief characterisation of these initiatives.

2.1 Smart and Sustainable cities

Over the last decades, a number of local initiatives (the "green city", "intelligent city", "knowledge city", etc.) aiming to improve the environmental, economic, and social conditions of urban areas have been put forward (Trindade *et al.* 2017). Among these, the "sustainable city" and the "smart city" emerged in the 1990s as part of the so-called "sustainable

[1] Wallonia is one of the three Belgian regions (Flanders and Brussels-Capital being the others), and the Belgian case is generally interesting because several policies have been launched in recent years to support the development of "smart initiatives" at different administrative levels. Still, most "smart city" initiatives in Belgium tend to be organised around regional programmes involving ICTs and developed at the municipality level (Desdemoustier *et al.* 2019, Esposito *et al.* 2021), hence our focus on the Wallonian municipalities.

development" and "smart growth" movements in US urban planning and design, respectively (Albino *et al.* 2015, Ahvenniemi *et al.* 2017, Bibri and Krogstieb 2017). Since then, they have spread to become global local initiatives in that "smart" and "sustainable" projects can be found in urban areas all over the world (Estevez *et al.* 2016, Collins *et al.* 2017). Also, while the "sustainable city" was the predominant initiative during the 2000s, the "smart city" has prevailed most recently (de Jong *et al.* 2015, Noori *et al.* 2020).

The "smart city" concept was initially closely linked to the application of ICTs to urban development projects, for technology was seen to be critical to facilitate bottom-up approaches and increase citizens' participation (Nam and Pardo 2011). However, this conceptualisation gradually evolved to embrace other elements that may impinge upon a city's performance (e.g., human capital) and/or citizens' wellbeing (e.g., environmental sustainability), although no general consensus has emerged on what a smart city is. Today many different definitions co-exist and, although technological, sustainable, and human capital elements tend to always be present, they differ in the importance given to each element (Caragliu *et al.* 2011, Caragliu and Del Bo 2015). In practice, this is because the stakeholders involved in launching such initiatives may differ in the way they conceptualise the smart city (Lombardi *et al.* 2012, Ching and Ferreira 2015) and/or contextual factors may exist that lead the stakeholders to prioritise one element or another (Nam and Pardo 2011, Neirotti *et al.* 2014). As a result, urban areas pursue the smart city concept differently, so that while some smart city initiatives are strongly technological and hardware-oriented (Washburn and Sindhu 2010), others put the emphasis on the sustainable orientation (Chourabi *et al.* 2012), and yet others adopt a more holistic view (Kummitha and Crutzen, 2017). Evidence from case studies shows that the sustainable and/or digital orientations of smart city initiatives are the most common (Manville *et al.* 2014, Angelidou 2017).

However, the debate over the sustainable city and the sustainability dimension of the smart city has recently regained importance, for urban areas have started to be seen not only as the source of many sustainability concerns but as the main field to develop sustainable solutions (Kennedy *et al.* 2014, Croci *et al.* 2017, Hultman *et al.* 2020). While for some "smart cities cannot be smart unless they are sustainable" (Yigitcanlar *et al.* 2019), others stress that "[t]o achieve sustainability, cities need to implement smart solutions enabled by smart technology" (Elgazzar and El-Gazzar 2017: 252). As a way to reconcile these conflicting views and bridge the differences between the "sustainable city" and "smart city" (Ahvenniemi *et al.* 2017, Martin *et* *al.* 2018), the term "smart sustainable cities" has emerged to describe smart city initiatives that seek to achieve the long-term sustainability of the urban environment by making extensive use of ICTs (European Commission 2012, Kramers *et al.* 2014, Lee *et al.* 2014).

A review of the literature on SSCs is beyond the scope of this paper (see e.g., Bibri and Krogstieb 2017). What is interesting to note here is that there is very limited evidence on whether *i)* SSCs make a difference in terms of sustainability outcomes and *ii)* sustainability is a main driver of the SSCs (Bansard *et al.* 2017, Haarstad 2017). Next, we discuss the main studies addressing these questions and, more generally, those analysing the effectiveness of global or transnational sustainability initiatives developed at the local level and the drivers of such local sustainability initiatives.

2.2 The effectiveness of transnational local sustainability initiatives

Despite the importance of global sustainability initiatives developed at the local level to reduce emissions and mitigate climate change (Hultman *et al.* 2020), "evidence of the effectiveness of these measures remains limited" (Kennedy *et al.* 2014: 345). Also, comparisons across studies are difficult because different aspects of these initiatives can be evaluated and different methodologies and data are used (Hsu *et al.* 2019). In this respect, if the goal is to empirically assess whether past commitments to sustainable initiatives result in an increase in the likelihood of achieving certain targets, then the most suitable statistical approach is to use regression models (Krause 2012a, Wang 2012, Yigitcanlar and Kamruzzaman 2018, Stephen *et al.* 2019, Hsu *et al.* 2020). This is the approach followed in this paper.

Within this limited literature, the dependent variable is either an actual sustainability outcome (Yigitcanlar and Kamruzzaman 2018, Hsu *et al.* 2020) or a proxy for a mitigation policy (Krause 2012a, Wang 2012, Stephen *et al.* 2019) and the main covariate is the engagement in a transnational sustainability initiative while controlling for other factors that may affect the outcome or policy analysed. Notice, however, that while Yigitcanlar and Kamruzzaman (2018), Stephen *et al.* (2019), and Hsu *et al.* (2020) only analysed transnational local sustainability initiatives, Krause (2012a) and Wang (2012) also considered a national one. Further, Hsu *et al.* (2020) and Stephen *et al.* (2019) analysed effectiveness in cities from different countries, whereas Krause (2012a), Wang (2012), and Yigitcanlar and Kamruzzaman (2018) concentrated on cities from a single country. Lastly, whereas Krause (2012a), Wang (2012), Hsu *et al.* (2020), and Stephen *et al.* (2019) assessed the impact of transnational local sustainability initiatives that explicitly aim to address climate change, Yigitcanlar and Kamruzzaman (2018) considered the role of smart cities for this purpose (as we do here). Next, we discuss these related papers in detail.

Hsu *et al.* (2020) evaluated 1,066 cities engaged in the EU Covenant of Mayors climate initiative in terms of the reduction in per capita emissions of CO_2 using a linear regression model. They identify six major thematic areas of climate policy strategies and actions that the cities adopted (using topic modelling techniques) to conclude that only “cities that have identified key actions specifically in energy efficiency are associated with higher GHG emission reductions” (p. 1019). They also found that cities with lower levels of ambition for a climate change commitment (that is, cities that had targeted less than 21% reduction) reduce on average more emissions per capita per year than the more ambitious cities. For the control variables, they used density, GDP per capita, population, baseline levels of emissions, national emissions reduction trend, and number of climate mitigation policies at the national level. Note that while baseline emissions account for differences in the scope to achieve emissions reductions (the higher the initial emissions per capita, the easier this is; see also Croci *et al.* 2017), national trends and policies are meant to control for differences in the institutional setting that may facilitate mitigation efforts (Saha 2009). This turned out to be critical in their empirical strategy, since these variables were found to be the main statistically significant determinants of the CO_2 reduction of emissions.

Stephen *et al.* (2019) evaluated the membership of five global municipal climate networks and two emissions-reporting platforms in 512 cities from all over the world that had a population of at least 1 million inhabitants. The evaluation was made in terms of their investments in renewables, using a dummy variable to indicate those cities with at least one solar photovoltaic project of more than 1 MW within the administrative city boundaries in the period 2015-2016, and a logistic regression model. Their results show that only the C40 network has a statistically significant effect on the low-carbon investment projects considered. For the control variables, the study used a binary variable to indicate whether previous investments in utility-scale solar photovoltaic projects had been made in the city, drivers of electricity demand (population and population growth), a proxy for solar photovoltaic potential (averaged annual solar irradiance), and country-level characteristics (GDP per capita, a market risk measure, and a dummy variable indicating the existence of solar-photovoltaic supporting policies). Previous investments, population, and GDP per capita were statistically significant covariates.

Also using proxies for the policy outcome, Krause (2012a) and Wang (2012) provide evidence from US cities on the effectiveness of committing to both a national (US Mayors Climate Protection Agreement) and a transnational (Cities for Climate Protection) sustainability initiative. To this end, Krause (2012a) analysed the number of climate-relevant actions (a maximum of 17 were considered) taken by 329 cities that answered a survey sent in 2010 to the 665 US cities with populations over 50,000, using propensity score matching, the Heckman selection model, and instrumental variables. Wang (2012) analysed dummy variables on the adoption of climate mitigation policies and measures taken by 174 and 185 Californian cities that provided such information to the California Governor's Office of Planning and Research's 2008 and 2009 Local Government Annual Planning Surveys, respectively, using probit models. Both Krause (2012a) and Wang (2012) found evidence supporting the effectiveness of transnational initiatives, but whereas the former did not find any statistically significant effect in joining a national initiative, the latter found the opposite with respect to the adoption of mitigation policies. For the control variables (see Krause 2012b for details), results across the different specifications considered by Krause (2012a) show the statistical relevance of interest groups' pressure (as represented by a proxy of the number of PhDs per 1,000 residents), government capacity (as represented by the proxies of population, per capita general revenue, a dummy variable for the presence of a sustainability coordinator on staff, and a dummy variable for the presence of an elected official or staff member who advocated greenhouse gas reducing activities) and regional policy (a dummy variable for high climate policy activity states). In contrast, none of the geographical and sociodemographic variables considered by Wang (2012) turned out to be statistically significant (we provide further details on the definition of these variables below).

Lastly, the only study that to the best of our knowledge has sought to analyse the effectiveness of smart cities as a mitigation strategy for emissions is Yigitcanlar and Kamruzzaman (2018). The study analysed the impact of the level of smartness, as measured by the number of websites hosted per 1000 population and internet protocol addresses per 1000 population (grouped by quartiles and both referring to 2017), on CO_2 emissions in fifteen UK cities over the period 2005 to 2013. This means that, strictly speaking, they provide evidence of the impact of future levels of smartness on current levels of emissions (for the years 2006 to 2013 when they interact their smartness measures with year dummies). This caveat aside, the study concludes (p. 56) that, after controlling for GDP, population density, green area, polycentricity, and urban sprawl, *i)* “there is a [positive and] statistically significant relationship between city smartness and CO2 emissions, *ii)* “the relationship is not linear, but tended to be U-shaped”, and *iii)* “there is no temporal effect of the city smartness on CO2 emissions”.

The study has three limitations that this paper seeks to address. First, the identification of smart cities is dubious, since it is only based on internet services (i.e., ICTs dimension) and does not account for other dimensions of the smart city (e.g., governance and quality of life) that are generally considered relevant (Neirotti *et al.* 2014, Caragliu and Del Bo 2015). Second, since the focus is rather on the ICT adoption, the important distinction between smart city initiatives following a digital and/or sustainable orientation is not considered (Manville *et al.* 2014, Estevez *et al.* 2016, Angelidou 2017). Third, the structure of the data does not allow the short-term impact of smart city initiatives on the quality of air to be properly identified (Krause 2012, Hsu *et al.* 2020). On the other hand, we share with Yigitcanlar and Kamruzzaman (2018) the use of direct metrics for the dependent variable and the analysis of municipalities from a single country.

2.3 Drivers of transnational local sustainability initiatives

There is extensive literature on the drivers of sustainability initiatives at the local level (see e.g., Hawkins *et al.* 2016).[2] In particular, a number of studies have empirically analysed the drivers of the commitment to national (Krause 2012a, Wang 2012) and transnational sustainability initiatives (Brody et al. 2008, Zahran *et al.* 2008a, Zahran *et al.* 2008b, Krause 2012a, Wang 2012) using regression analyses (as we do here). In this respect, notice that all these studies analysed the same transnational sustainability initiative in US administrative units. Namely, the Cities for Climate Protection in US cities (Krause 2012a and Wang 2012, the latter limited to California), metropolitan areas (Zahran *et al.* 2008a), and counties (Brody *et al.* 2008, Zahran *et al.* 2008b). Note, however, that none of these papers analysed the drivers of SSCs as a transnational local sustainability initiative (as we do here). Next, we discuss these related papers in detail.

[2] This includes analyses of the drivers of the commitment of human and financial resources to sustainability (Hawkins *et al.* 2016; see also Wang *et al.* 2012) and the drivers of the adoption of sustainability policies (Wang 2012), mitigation measures (Krause 2012a, Wang 2012; see also Wang *et al.* 2012), and a combination of both using an index or ranking (Saha 2009, Krause 2012a, Prado *et al.* 2012).

A critical feature of the commitment of urban areas to (trans)national sustainability initiatives is that such commitment is usually voluntary and low (Zeppel 2013).[3] Also, the municipalities involved face a collective action problem: the costs of the initiatives will be paid locally, but the benefits will not be limited to the local area because of their nonexcludable and nonrival nature. To the extent that these local efforts cannot completely prevent the impact of global climate change (and there are usually no regional or national offsetting policies), the question that arises is why urban areas would commit to such sustainability initiatives (Brody *et al.* 2008, Zahran *et al.* 2008a, 2008b). The main difference in the empirical studies addressing this question are the factors that are considered to drive this decision, which is usually measured by a dichotomic variable and consequently analysed using binary (linear or probit) models (the only exception being Zahran *et al.* (2008a) who considered the percentage of population in jurisdictions committed to the initiative as the variable of interest and so used linear regression models).

Brody *et al.* (2008) and Zahran *et al.* (2008a, 2008b) considered three sources of incentives or drivers of commitment. First, the extent to which the urban area is vulnerable to “climate change risks” (e.g., coastal proximity and susceptibility to extreme weather events). Second, the extent to which the area produces “climate change stress” (e.g., by carbon-intensive industrial, transportation, energy, and production practices). Third, the extent to which the urban area is civically equipped to create “opportunities for climate policy action” (e.g., human social capital and local concern for the environment). Results in Zahran *et al.* (2008a) show that the climate change stress (negative effect) and the civic capacity (positive effect) z-scores of the variables employed as a proxy for these factors were statistically significant drivers, whereas results in Brody *et al.* (2008) and Zahran *et al.* (2008b) provide statistical support for the three sources of incentives, both in the urban areas considered and the (spatially weighted) neighbouring jurisdictions (Brody *et al.* 2008).

Wang (2012) reframed the political economy approach of Brody *et al.* (2008) and Zahran *et al.* (2008a, 2008b) and proposed drivers that are arguably relevant for the demand and supply of the adoption of climate policies and mitigation actions. Thus, demand variables included voter preferences (percentages of registered Democrats and Green Party voters), potential for

[3] Note, however, that empirical evidence shows that urban areas involved in (trans)national initiatives on average commit more resources to sustainability (Hawkins *et al.* 2016), are more likely to adopt sustainability policies (only in the case of transnational initiatives according to the results reported by Krause 2012a) and, in the case of transnational initiatives, are more likely to adopt mitigation measures (Wang 2012).

perceived local co-benefits (air quality), and perceived vulnerability to climate change (a coastal dummy as well as rainfall and temperature measures), whereas supply variables referred to the local government's administrative capacity (population) and technical expertise (per capita number of planning professionals). The results show that sociodemographic variables (population, income, and percentages of registered Democrats and Green Party voters) had a positive and significant effect on the likelihood of joining both the national and transitional initiatives considered. In contrast, "climate change risks" were not statistically significant. Interestingly, good air quality (as measured in 2008) had a statistically significant negative effect on the likelihood of joining the transnational initiative but it was not statistically significant for the national one.

Lastly, Krause (2012a) followed an empirical approach to the selection of drivers, since she refers to a previous study in which several theories on the drivers of local political decision-making are tested (Krause 2012b). The drivers considered are proxies for interest groups' pressure (income, education, percentage of local votes cast for the Democratic candidate, percentage of jobs in manufacturing, and a dummy for the presence of an identifiable push for climate protection from members of the local public), government capacity (population, per capita general revenue, a dummy for the presence of a sustainability coordinator on staff, and a dummy for the presence of an elected official or staff member who advocated greenhouse gas reducing activities), and a dummy identifying cities in states with high levels of climate policy activity. The results show that the percentage of local votes cast for the Democratic candidate, population, and the dummies for the presence of a sustainability coordinator on staff and an elected official or staff member who advocated greenhouse gas reducing activities were common drivers of the national and transnational initiatives considered; income and education (percentage of population over the age of 25 with a BA or higher) were statistically significant drivers of the transnational initiative only; and the number of PhDs per 1,000 residents and the dummy for the presence of an identifiable push for climate protection from members of the local public were statistically significant drivers of the national initiative only.

This paper adds to this limited literature by analysing the drivers of SSCs that follow a digital and/or sustainable orientation. In particular, we aim to analyse the role of past air quality as a driver of the smart city initiatives that follow a sustainable orientation (Wang 2012). In addition, we complement previous studies by exploring the role of economic and political drivers that have been found to be relevant in related analyses on the sustainability initiatives at the local level (Saha 2009, Pardo *et al.* 2012, Wang *et al.* 2012). Lastly, following the smart city literature we explore the role of stakeholders' involvement as a driver of the sustainable orientation of smart cities (Nam and Pardo 2011, Albino *et al.* 2015).

3. Methods and data

This paper aims to provide evidence from Wallonian municipalities for two research questions derived from the previous literature review. First, is air quality a target of SSC initiatives? More precisely, are current levels of air quality at the local level driven by past smart city initiatives, possibly following a sustainable orientation, after controlling for other factors that have been found to affect analogous sustainable outcomes? Second, is air quality a trigger for SSCs? More precisely, are current smart city initiatives that follow a sustainable orientation (rather than other alternatives such as digital, sustainable and digital, and neither one nor the other) driven by past levels of air quality at the local level after controlling for other factors that have been found to affect the commitment to transnational local initiatives? Next we discuss the methods and data used to address these research questions.

3.1 Methods

We use regression models to empirically address our research questions because we ultimately seek to estimate the impact of a variable of interest (past implementation and orientation of smart city initiatives and levels of air quality) on a sustainability and SSC outcome (air quality and smart city orientation, respectively) while controlling for other factors that may affect such outcome. This means that air quality in the "effectiveness of the SSCs model" and smart city orientation in the "drivers of the SSCs model" are our dependent variables, whereas past implementation and orientation of the smart initiatives and past air quality, respectively, act as key explanatory factors. Notice also that the other covariates included in the models seek to replicate the set of drivers discussed in our review of the literature and consequently act as control variables. Lastly, because of the continuous and discrete nature of our dependent variables, respectively, we use linear and discrete choice regression models (see e.g., Wooldridge 2010 for details on these regression methods).

In particular, the effectiveness of the SSC model corresponds to the following linear specification:

$$AQ = \beta_1 + \beta_2 SC + \beta_3 X_{AQ} + \epsilon,$$

where AQ denotes a sustainability outcome (in our case, air quality), SC denotes measures of implementation and orientation of smart city initiatives, X denotes a set of control variables, and ϵ is the error term (an unobservable and independently distributed variable whose conditional expectation given the regressors is zero). The coefficients of the model are β_1, β_2 and β_3, being β_2 the coefficient of interest to test the hypothesis that air quality is a target of SSC initiatives (i.e., they may be acting as a transnational local sustainability initiative). These coefficients were estimated by the method or ordinary least squares.

As for the drivers of the SSC model, the multinomial logit specification has response probabilities given by

$$\Pr(\text{SC orientation} = j) = \exp(\gamma_{1j} + \gamma_{2j}AQ + \gamma_{3j}W)/\left[1 + \sum_{h=1}^{3}\exp(\gamma_{1h} + \gamma_{2h}AQ + \gamma_{3h}W)\right]$$

where *j* denotes the different SC orientations considered (digital, digital & sustainable, and neither digital nor sustainable, being sustainable the reference category), W denotes a set of control variables, and the error term (of the underlying utility function) is an independently distributed variable following a type I extreme value distribution. The coefficients of the model are γ_{1j}, γ_{2j} and γ_{3j}, being γ_{2j} the coefficients of interest to test the hypothesis that air quality is a driver of the smart city initiatives that follow a sustainable orientation. These coefficients were estimated by the maximum likelihood method.

3.2 Data

To address our research questions, we required an institutional setting that shows enough variation in the implementation and orientation of smart city initiatives. This makes the Wallonian smart cities an interesting case to study.[4] First, several policies have been launched in Belgium to support the development of smart initiatives at different administrative levels. These include “Digital Belgium”, launched in 2013 at the federal level; “Smart Flanders” and “Digital Wallonia” at the regional level and launched in 2017 and 2015, respectively; and the smart city projects of Antwerp, Brussels, and Namur at the local level, all launched around the

[4] Ideally, we would also like to claim that the SSCs in Wallonian municipalities are largely representative of smart city initiatives globally. We do not have any evidence supporting this claim, but we can argue, following previous related studies (Neirotti *et al.* 2014, Estevez *et al.* 2016, Angelidou 2017), that our results are likely to hold for analogous institutional settings.

years 2012-2014. Second, most SC initiatives in Belgium tend to be organised around regional programs involving information and communication technologies. In the Wallonian region, for example, the strategy of the regional government for the 2015 to 2018 period ("Digital Wallonia", later extended to the 2019-2024 period) focused on four areas of activity: support to digital enterprises, digitalisation of the public administration, strengthening of the ICT infrastructures, and improvement of digital literacy skills (Esposito *et al.* 2021). Third, despite the marked digital orientation of both the federal and regional policies, Desdemoustier *et al.* (2019: 133) show that many municipalities in Wallonia have launched smart city initiatives following a holistic approach in which not only technological but sustainable, governance, and human and social capital factors matter.

In particular, to empirically address our research questions we required data on *i)* air quality, *ii)* smart and sustainable city initiatives, and *iii)* the drivers discussed in the literature review section. Panel A in Table 1 provides descriptive statistics of the variables used as proxies for air quality and the smart and sustainable city initiatives. Panel B in Table 1 does the same but for our set of drivers or control variables: first those of the effectiveness of the SSCs model and then those of the drivers of the SSCs model (that do not act as control variables in the SSCs model, to avoid unnecessary repetitions). In the next two sub-sections we provide definitions of these variables and details on the statistical sources reported in the last column of Table 1. In essence, our data set is similar to the one used by Krause (2012a, 2012b) in that it contains information from a survey and official statistics. It differs, however, in the longitudinal information on the air quality variable, which is similar to the one used by Hsu *et al.* (2020).

[Insert Table 1 about here]

3.2.1 Variables of interest: air quality and SSC indicators

Our air quality measure is an index computed by the Walloon Air and Climate Agency (*Agence Wallone de l'air & du climat*) that combines levels of ozone (O_3), nitrogen dioxide (NO_2), and particulate matter of different diameters ($PM_{2.5}$ and $PM_{10-2.5}$, in micrometres). For each gas and particulate matter, data was collected by 23 automatic stations spread over Wallonia and then spatially interpolated to obtain the values for each municipality.[5] Then, a daily index was

[5] The interpolation method was empirically validated by a local study on the area of Charleroi in the years 2008 to 2010. The report in French can be found at http://193.190.182.213/WebAirQuality/RapportEtudes.aspx. Also, the geographical distribution of the 23 stations can be found at https://www.wallonair.be/fr?mode=complet.

computed using the difference between the daily average values of the municipality and that of the regional average, divided by the regional standard deviation. Finally, a yearly average was computed for each gas and particulate matter. The average of these values, averaged again over three-year periods, is the index of the quality of air we used. Data is available for each year of the period 2010 to 2017, i.e., eight three-year period averages were available, starting from 2010-2012 up to 2017-2019. Importantly, since the index is constructed using the regional average as the reference value (i.e., zero), negative and positive values indicate a better and worse quality of air, respectively.

We used two approaches to the identification of the smart and sustainable initiatives. First, following Neirotti *et al.* (2014) and Caragliu and Del Bo (2015) we used participation in the € 4 million "Smart Region Territoire intelligent" programme launched in January 2019 by the Wallonian government ("to encourage Wallonian [municipalities] to develop digital projects, in energy and environment, mobility, or even governance and citizen participation") to identify smart city initiatives using a binary variable. A total of 99 municipalities out of the 262 in Wallonia were involved in the projects submitted. Participants who responded to the call basically did so to obtain funding for their "smart city" projects, so we expect this variable to reflect smart city initiatives associated to the factors explicitly mentioned in the call: transport & ICT (digital, energy and mobility), environment, and governance & participation.

Second, following Ching and Ferreira (2015) we identified smart city initiatives using survey data and an assessment from a local public official who "is responsible for the projects associated with the phenomenon of the smart city in the municipality" (Bounazef *et al.* 2018). The survey was carried out in 2017 by the Smart City Institute of the University of Liège and targeted all 589 Belgian municipalities (no coverage error). There was a response rate of nearly 21% and the 123 local councils who participated in the survey are statistically representative of the Belgian population of municipalities in terms of degree of urbanisation (urban *vs.* rural, using the OECD's threshold of 150 inhabitants per km^2) and political organisation (provinces and regions) according to the Chi-Square adjustment test.[6] We thus used the information provided by the 61 Wallonian municipalities (see Figure 1 for a geographical distribution). Note

[6] On the other hand, the sample overrepresents municipalities with more than 50,000 inhabitants (they are about 16% of the sample but only 5% of the Belgian municipalities), which is consistent with larger municipalities being more inclined to pursue smart city initiatives (Manville *et al.* 2014).

that, out of the 99 municipalities that participated in the "Smart Region Territoire intelligent" programme, 37 responded to the survey.

[Insert Figure 1 about here]

Compared to the participation variable, the survey provides more detailed information on the level and orientation of the smart city initiatives. First, we used the answer to the question "Please indicate the level of evolution of your municipality in the process of smart city implementation" using an integer scale between 1 ("Our municipality is not a smart city") and 9 ("We are a smart city") as a measure of the level of smart city implementation reached by the municipality (0 being "Don't know" and/or "Not applicable"). Second, we used the answer to the question "What are the elements that your municipality associates with the smart city?" to construct indicator variables of the smart city orientation, thus distinguishing between sustainable (9 municipalities), digital (10), sustainable and digital (26), and neither sustainable nor digital (16) orientations. Also, these categories define our dependent variable for the drivers of the SSCs model (see Table 3).

The use of these two sources of data allowed us to assess the robustness of our results to alternative identification strategies of the smart city. However, they also convey information from slightly different time periods. On one hand, the participation variable probably picks up smart city developments occurring during the years previous to the call (i.e., 2017-2018), for although the programme was launched in early 2019, the projects and plans included in the applications had to be decided earlier. On the other hand, the information from the survey probably reflects initiatives that took place over the 2014 to 2016 period, since to our knowledge the oldest plan for a Belgian municipality that integrates smart city initiatives dates from 2013 and the survey was carried out during the first part of 2017.[7]

3.2.2 Control variables

In the effectiveness of the SSCs model, we initially used the share of woodland in 2015, density of population in 2015, and taxable income in euros over total population in thousands in 2015 as control variables. This largely follows Yigitcanlar and Kamruzzaman's (2018) model

[7] It is also interesting to note that the Wallonian municipalities that participated in the regional smart programme are likely to be in advanced stages of the continuum that defines a smart city (Nam and Pardo 2011). In fact, the 37 participants in the programme that answered the survey have on average higher values in the level of implementation variable than the other 24 Wallonian municipalities in the survey.

specification, although these variables are also considered by other studies on the effectiveness of transnational local sustainability initiatives (see Section 2.2). Then we extended the set of regressors by including those proposed by Hsu *et al.* (2020): population in 2017, baseline levels of emissions, national emissions reduction trend, and number of climate mitigation policies at the national level. Unfortunately, we could not find information on either the national emissions reduction trend or the number of climate mitigation policies at the national level. However, we managed to gather information on proxies for these variables at the regional level (which is ultimately our institutional unit of reference). First, since the air quality index we used is constructed with respect to the regional level, differences in the air quality index between 3-years periods account for both baseline levels and the regional trend. In particular, negative values of such an emissions trend would indicate an improvement in the quality of air between the periods considered (positive differences obviously indicating the opposite). Second, we used the rate of participation of the municipality in 10 environmental programmes developed at the regional level over the last decades to account for previous climate mitigation policies.[8] Lastly, we explored the idea that past air quality, as measured by the emissions trend, is a proxy for the local co-benefits of sustainability policies and mitigation actions (Wang 2010). Given that we hypothesised that SSCs may be acting as a transnational local sustainability initiative, this would mean that the potentially mitigating effects of such initiatives could be reinforced by a positive perception of their local co-benefits. We addressed this idea by including the product between the emissions trend and the smart city initiatives variables (participation, level of implementation, and orientation) as an additional regressor.

For the drivers of the SSCs model, our first set of controls sought to replicate those proposed by Brody *et al.* (2008) and Zahran *et al.* (2008a, 2008b). Thus, we used the air quality index for the 2014 to 2016 period, the share of woodland in 2015, and the average rainfall of the 1991-2020 period to account for the extent to which the urban area is vulnerable to "climate change risks" (Zahran *et al.* 2008a, Krause 2012a, Wang 2012); density of population in 2015, number of private vehicles per household in 2015, number of kilometres of motorways in the municipality in thousands in 2017, and the share of green firms (computed as the number of

[8] Data provided by the *Service public de Wallonie* (see http://etat.environnement.wallonie.be/contents/indicatorsheets/FFH 17.html for details in French). The 10 programmes considered are (year of launching in brackets): "Semaine de l'arbre" (2003), "Contrat de rivière" (1993), "Fauchage tardif des bords de routes" (1995), "Plan Maya" (2011), "Opération combles et clochers" (1995), "Plan communal de développement de la nature" (1995), "Projet AlterIAS" (2010), "Cimetière Nature" (2015), "Conseiller en environnement subventionné par le SPW" (2008), and "Parc naturel" (1979).

firms in green industries, as defined by the methodology proposed by Shapira *et al.* (2014), over total number of firms in the 2013-2018 period and using data from Bel-first and Bureau van Dijk) to account for the extent to which the area produces "climate change stress" (Brody *et al.* 2008, Zahran *et al.* 2008a); and taxable income in euros over total population in 2015 and the rate of population with a university degree in 2011 to account for the extent to which the urban area is civically equipped (Brody *et al.* 2008, Zahran *et al.* 2008a, Zahran *et al.* 2008b, Krause 2012a, Wang 2012). We then extended the set of regressors by including political and economic factors proposed by Saha (2009) and Prado *et al.* (2012). Namely, percentage of seats at the local council obtained by the leading party in the municipal elections of 2018, number of electoral lists in the municipal elections of 2018, and the unemployment rate in 2016. Lastly, to account for the capacity factors proposed by Wang (2012) and Wang *et al.* (2012) we included population in 2017 and the rate of participation of the municipality in 10 environmental programmes developed at the regional level over the last decades as a proxy for managerial capacity, whereas to control for the stakeholders' involvement in smart sustainable initiatives (Nam and Pardo 2011 and Albino *et al.* 2015) we used the median implication of different stakeholders.[9]

4. Results

In this section we first present the estimates we obtained on the relation between air quality and the implementation and orientation of smart city initiatives (ordinary least squares estimates of the effectiveness of the SSCs model, reported in Table 2) and smart city orientation and past air quality (maximum likelihood estimates of the drivers of the SSCs model, reported in Table 3). We then discuss the outcomes of some robustness tests.

4.1 Basic Estimates

The first thing to notice about the results reported in Table 2 is that negative/positive coefficient estimates indicate a positive/negative effect on the quality of air. This is because negative/positive values of the dependent variable indicate a better/worse quality of air and, with the exception of the emissions trend discussed below, all the covariates are either dummies or take positive values. Also, coefficient estimates show analogous signs and statistical significance when using alternative proxies for the smart city initiatives (a dummy indicating

[9] As measured from the answers to the Smart City Institute survey (see subsection 3.2.1) question "What is the level of implication of the following agents in the public sector, the private sector, and civil society in the smart city projects launched by your municipality?", the answers being coded 0 = "Don't know", 1 = "Strong implication", 2 = "Average implication", and 3 = "Weak or non-existent implication".

the participation in a regional smart city programme in columns (i), (iii), and (v), the level of implementation of smart city initiatives in columns (ii), (iv), and (vi), and the smart city orientation dummies in column (vii) of Table 2). Lastly, the best fit is found in columns (v) and (vi), where we report results from the inclusion of the product between the emissions trend and the smart city initiatives variables as additional regressors.

[Insert Table 2 about here]

Columns (i) and (ii) of Table 2 seek to replicate the model specification proposed by Yigitcanlar and Kamruzzaman (2018) and thus report the current value of the dependent variable (quality index for the 2015 to 2017 index) and the smart city variables squared, whereas columns (iii) and (iv) do so for the model specification proposed by Hsu *et al.* (2020) and report the future value of the dependent variable (quality index for the 2017 to 2019 index) and do not include the squared term. Results are largely consistent with those reported in these related studies in that the share of woodland and the emissions trend both show a positive effect on air quality, whereas density and income show the opposite effect. However, we differ from Yigitcanlar and Kamruzzaman (2018) in that we did not find any statistically significant relation between smart city initiatives, either in linear or non-linear (squared) form, and quality of air. We also differ from Hsu *et al.* (2020) in the statistical significance of density (when using the participation dummy) and income.

These results largely hold when the product of the emissions trend and the smart city initiatives variables (i.e., the participation dummy, the level of implementation, and the orientation dummies) are included in columns (v), (vi), and (vii) of Table 2. Also, since (some of) these products are statistically significant, they show that, depending on the scope to achieve emissions reductions approximated by the emissions trend, the smart city initiatives may result in better or worse levels of air quality. Specifically, estimates in column (v) indicate that, with respect to those municipalities not engaged in smart city initiatives in Wallonia, municipalities engaged in smart city initiatives with a positive/negative trend (indicating low/high levels of past air quality, respectively) have on average a better/worse quality of air (i.e., the index decreases/increases). For those reported in column (vi), they indicate that municipalities with a positive/negative trend have higher/lower levels of air quality the higher/lower the level of implementation of smart city initiatives. Lastly, estimates reported in column (vii) indicate that, with respect to those municipalities engaged in smart city initiatives following a sustainable, digital, and sustainable and/or digital orientation, municipalities following neither a sustainable nor a digital orientation with a positive/negative trend have on average a worse/better quality of air.

We now analyse the estimates of the drivers of the SSCs model reported in Table 3.These are coefficient estimates, but we also report average marginal effects (AME) evaluated at the mean of the explanatory variables for the effect of the air quality index on the probability of each smart city orientation being followed at the bottom of Table 3. Both outputs are reported for three alternative specifications: columns (i) to (iv) seek to replicate the model specification proposed by Zahran *et al.* (2008a, 2008b), columns (v) to (viii) extend the set of regressors by including the political and economic factors proposed by Saha (2009) and Prado *et al.* (2012), and columns (ix) to (xii) extend it further by including our proxies for managerial capacity and stakeholders' involvement (Nam and Pardo 2011, Wang 2012, Wang *et al.* 2012, Albino *et al.* 2015).

[Insert Table 3 about here]

We start by noting that the Wald test reported at the bottom of the table supports the joint-significance of the proposed drivers. Individually, the share of woodland, rainfall, income, education, unemployment, and the stakeholders' involvement arise as common drivers of the smart city initiatives orientation. In particular, a municipality is more likely to follow a sustainable orientation (rather than the other alternatives considered) the higher its share of woodland, density, income, and unemployment and the lower the rainfall, education level, and stakeholders' involvement. Notice, however, that certain "climate stress", political, and capacity factors are differential drivers of the digital and digital & sustainable orientations. It is also interesting to note that the effects that these drivers have on the log-odds of each alternative differ, often substantially. To illustrate, a one per cent increase in the share of woodland of a municipality would, *ceteris paribus*, cause a 0.59 decrease in the relative log-odds of following a digital versus a sustainable orientation, but it would only cause a 0.41 decrease in the same relative log-odds of the digital and sustainable orientation.

We conclude our analysis of the results reported in Table 3 by considering the estimates of the average marginal effects (AMEs) of the air quality variable. However, given that the best fit is found in the last specification, we concentrate on the AMEs reported in columns (ix) to (xii).

These are (practically) all statistically significant, which indicates that air quality and thus sustainability is a major driver of SSCs. In particular, their signs indicate that whereas having a better/worse quality of air than the average Wallonian municipality (i.e., negative/positive values of the index) positively/negatively affects the probability that a municipality follows sustainable and digital orientations, it negatively/positively affects the probability that a municipality follows digital & sustainable and neither digital nor sustainable orientations.

4.2 Robustness tests

We performed a number of robustness tests (in the form of changes in the dependent and/or explanatory variables) on the results reported in Tables 2 and 3. First, one may argue that an important limitation of the model specifications proposed by Yigitcanlar and Kamruzzaman (2018) and Hsu *et al.* (2020) is that they do not control for some of the main sources of global greenhouse gas emissions (Kennedy *et al.* 2012, Kennedy *et al.* 2014). Namely, the sectorial structure of the firms located in the municipality (Saha 2009) and the importance of the transportation sector (Croci *et al.* 2017). Thus, we included the share of green firms and the number of vehicles per household as additional control variables in the effectiveness of the SSCs model. In addition, we included the average hours per day of sunshine in the 1990 to 2020 period (from the "Institut royal météorologique") as a proxy for energy use (Stephen *et al.* 2019). Second, in the drivers of the SSCs model, we replaced the air quality index for the 2014 to 2016 period by the indices computed for the years 2015 to 2017 and 2010 to 2012. Further, we replaced the share of woodland by the share of parks and gardens in 2015 (from Belfius 2007, 2017), included the difference between the average maximum and minimum temperature of the 1991-2020 period (from the "Institut royal météorologique") as an additional "climate change risks" variable (Brody *et al.* 2008, Zahran *et al.* 2008b), and the number of new green firms (computed using the methodology proposed by Shapira *et al.* (2014) and data from Bel-first and Bureau van Dijk) as an additional "climate stress" or "civic capacity" variable.

All these changes in the specification of our regression models obviously altered the values and significance of some of the coefficients in the regressions (results available upon request). However, the conclusions that can be extracted from these additional results do not substantially vary from the ones previously discussed. In particular, the signs and statistical significance of the air quality and smart city variables barely changed (while in general the fit of the models did not improve).

5. Discussion of results

Cities are responsible for most of the energy-related greenhouse gas emissions. At the same time, however, many emissions-reduction initiatives take place at the local level. Given the collective action dilemma that usually characterises such initiatives, the question that arises is what can possibly drive local stakeholders into such initiatives. What kind of economic and political factors lie behind them? Perhaps more importantly, are these initiatives successful? Do we observe improvements in sustainability outcomes following the implementation of these initiatives? The answers to these questions remain elusive, for empirical assessments of the effectiveness of these initiatives and/or the political, economic, and managerial factors that may drive them are scarce. This paper addresses this gap in the literature by studying the relation between air quality and past implementation and orientation of the smart initiatives (effectiveness of the SSCs model) and smart city orientation and past air quality (drivers of the SSCs model) in Wallonian municipalities.

In the effectiveness of the SSCs model, the negative (and sometimes statistically significant) sign of the emissions trend is consistent with the interpretation that baseline levels of air quality act as a proxy for the scope to achieve emissions reductions (Croci *et al.* 2017, Hsu *et al.* 2020). Since low/high baseline levels provide more/less scope for improvement, a positive/negative emissions trend (i.e., low/high baseline levels) positively/negatively impacts current levels of air quality (thus reducing/increasing the index). However, they also support the interpretation of the emissions trend as a proxy for the perceived co-benefits and risks of past sustainability initiatives (Wang 2012). From this perspective, stakeholders of municipalities with high/low baseline levels of air quality have a low/high perception of the local co-benefits of sustainability policies and mitigating strategies, thus being more likely to be less/more engaged in such policies and strategies in the future. As a result, municipalities with high/low baseline levels of air quality are less/more likely to succeed in the implementation of sustainability policies and mitigating strategies (Wald *et al.* 2012).

The negative and statistically significant coefficient of the product of the emissions trend with the smart city initiatives variables can be interpreted along the same lines (Nam and Pardo 2011and Albino *et al.* 2015). In the case of the participation and level of implementation variables, since the emissions trend is no longer significant (see columns (v) and (vi) of Table 2), results suggest that a strong commitment to the smart city initiatives is a means to engage stakeholders in sustainability policies and mitigating actions. In the case of the smart initiatives' orientation dummies, since the emissions trend is now (almost) statistically significant (see column (vii) of Table 2) results indicate that the positive/negative effects of the low/high baseline levels on air quality are mitigated in those smart cities that do not have a clear (sustainable and/or digital) orientation. One possible explanation for this might be that those municipalities whose smart city initiatives do not have a clear (sustainable and/or digital) orientation are not capable of achieving a sufficient level of engagement from the stakeholders. On the other hand, for those municipalities that have a clear (sustainable and/or digital) orientation and thus are capable of engaging the stakeholders, the positive/negatives effects of the low/high baseline levels on air quality remain.

It is also interesting to note that the smart city initiatives following a sustainable orientation (i.e., SSCs) have distinct drivers and that the impact of these drivers on the likelihood of following the sustainable orientation (rather than a digital, digital & sustainable, and neither digital nor sustainable) differs across the alternative orientations considered. This means that the "smart city" and the "sustainable city" are not interchangeable categories and, as a result, "the policy application of each of these city categories could be expected to be different" (de Jong *et al.* 2015: 26). In addition, results show that although the political economy framework proposed by Brody *et al.* (2008) and Zahran *et al.* (2008a, 2008b) provides a good starting point to analyse the drivers of the SSCs, it may not suffice. The statistical significance of unemployment and stakeholders' involvement across alternatives suggests that economic and capacity-building factors may help to better explain why certain smart city orientations are followed (Saha 2009, Pardo *et al.* 2012, Wang *et al.* 2012). A digital & sustainable orientation, for example, may require a higher level of stakeholders' involvement than a sustainable one. This may be critical for local governments aiming to pursue a certain orientation in their smart city initiatives.

All in all, the results show that the relationship between air quality and SSCs is complex (at least in the Wallonian municipalities). On the one hand, smart city initiatives can have a positive effect on the quality of air. However, for this to happen the municipalities engaged in these initiatives must have low baseline levels of air quality and either a strong commitment to the initiatives or follow an orientation that is (clearly) sustainable and/or digital. Alternatively, municipalities can also succeed in improving the quality of air if they have high baseline levels of air quality and follow an orientation that is neither (clearly) sustainable nor digital. This suggests that in those cases SSCs may be acting as an effective transnational local initiative for sustainability. On the other hand, past air quality is clearly associated with the smart city initiatives, regardless of their orientation. In particular, a better quality of air is likely to push future smart initiatives towards a sustainable orientation, i.e., SSCs. However, there is also a non-negligible chance that it pushes such initiatives towards a digital orientation, thus making the initiative more "smart" than "sustainable". This supports the view that while sustainability is the principal element for the development of SSCs, the role of technology cannot be underestimated.

Still, our empirical approach has a number of limitations. First, the lack of longer longitudinal data precludes a more sophisticated analysis of the dynamics of these relations. Second, we concentrate on a single sustainability outcome, which means that our results may not extend to alternative measures of sustainability (i.e., other outcomes and/or more complex measures). Finally, while we find that it is the combination of appropriate smart city initiatives and baseline levels of sustainability that causes an improvement in air quality, we do not empirically address the sources of this complex effect.

6. Conclusions

This paper concerns the recent phenomenon of the "smart sustainable cities", which can roughly be identified with territories that launch projects associated with the mobility of citizens and vehicles, big data and its technologies, and/or the increase of citizens' political participation, but always looking carefully at the long-term sustainability effects that such projects may have. In particular, we studied the role of the quality of air in Wallonian municipalities participating in a regional call for smart city projects (full sample) and self-reporting engagement in smart city initiatives following a sustainable and/or digital orientation (survey sample), both as target and trigger of such initiatives. Our assessments are based on results from regression and multinomial logit models whose specification closely followed the literature.

Our results reveal a complex relation between air quality and SSCs in Wallonian municipalities. Notably, we find that smart city initiatives may pay off in terms of sustainability outcomes. However, this generally requires an appropriately-oriented and strong commitment to these initiatives. This may seem quite demanding, but for local governments engaged or considering engaging in smart city initiatives these are at least encouraging news. We also find that air quality is an important driver of the smart and sustainable initiatives. In particular, municipalities with a good quality of air are more likely to engage in smart city initiatives that follow a sustainable orientation. However, our results do not rule out the possibility that "smart municipalities" with an analogous quality of air end up following a digital rather than a sustainable orientation.

How long the effects observed in our data last and how the effects decay are questions that will hopefully be addressed in future research. It will be also interesting to explore the relationship between SSCs and either a comprehensive sustainability index or other sustainability measures (e.g., energy saving). Finally, disentangling the combined effect of appropriate smart city initiatives and baseline levels of sustainability on air quality may provide a better understanding of the effects of SSCs on sustainable outcomes.

References

Albino, V., Berardi, U., and Dangelico, R.M. (2015): "Smart cities: Definitions, dimensions, performance, and initiatives", *Journal of Urban Technology*, **22**: 3-21. https://doi.org/10.1080/10630732.2014.942092

Angelidou, M. (2017): "The role of smart city characteristics in the plans of fifteen cities", *Journal of Urban Technology*, **24**: 3-28. https://doi.org/10.1080/10630732.2017.1348880

Ahvenniemi, H., Huovila, A., Pinto-Seppä, I., and Airaksinen, M. (2017): "What are the differences between sustainable and smart cities?", *Cities*, **60**: 234-245. https://doi.org/10.1016/j.cities.2016.09.009.

Bibri, S.E., and Krogstie, J. (2017): "Smart sustainable cities of the future: An extensive interdisciplinary literature review", *Sustainable Cities and Society*, **31**: 183-212. https://doi.org/10.1016/j.scs.2017.02.016.

Bansard, J.S., Pattberg, P.H., & Widerberg, O. (2017): "Cities to the rescue? Assessing the performance of transnational municipal networks in global climate governance", *International Environmental Agreements*, **17**: 229-246. https://doi.org/10.1007/s10784-016-9318-9

Belfius (2007, 2017): *Typologie socio-économique des communes*. https://research.belfius.be/fr/typologie-des-communes/

Bounazef, D., Desdemoustier, J., and Crutzen, N. (2018): *Smart cities in Belgium*, Smart City Institute, Université de Liège. http://labos.ulg.ac.be/smart-city/en/downloads-smart-city-barometers/

Caragliu, A., Del Bo, C., and Nijkamp, P. (2011): "Smart cities in Europe", *Journal of Urban Technology*, **18**: 65-82. https://doi.org/10.1080/10630732.2011.601117

Caragliu, A., and Del Bo, C. (2015): "Smart specialization strategies and smart cities: An evidence-based assessment of EU policies", in K. Kourtit, P. Nijkamp, and R. Stough (eds.), *The rise of the city*, Edward Elgar.

Caragliu, A., and Del Bo, C. (2018): "The economics of smart city policies", *Scienze Regionali*, **17**: 81-104. https://doi.org/10.14650/88818

Caragliu, A., and Del Bo, C. (2019): "Smart innovative cities: The impact of smart city policies on urban innovation", *Technological Forecasting and Social Change* **142**, 373-383. https://doi.org/10.1016/j.techfore.2018.07.022

Ching, T.-Y., and Ferreira, J. (2015): "Smart cities: Concepts, perceptions and lessons for planners", in S. Geertman *et al.* (eds.), *Planning support systems and smart cities*, Springer International Publishing.

Chourabi, H., Nam, T., Walker, S., Gil-Garcia, J.R., Mellouli, S., Nahon, K., Pardo, T.A., and Scholl, H.J. (2012): "Understanding smart cities: An integrative framework", *Proceedings of the 45th Hawaii International Conference on System Sciences*: 2289-2297. https://doi.org/10.1109/HICSS.2012.615

Collins, A., Leonard, A., Cox, A., Greco, S., Torrisi, G. (2017). "Report on smart cities and resilience: Perception and evaluation of regional and cohesion policies by Europeans and identification with the values of Europe" (PERCEIVE), GA No. 693529.

https://cordis.europa.eu/project/id/693529/en?format=pdf
Croci, E., Lucchitta, B., Janssens-Maenhout, G., Martelli, S., and Molteni, T. (2017): “Urban CO2 mitigation strategies under the Covenant of Mayors: An assessment of 124 European cities”, *Journal of Cleaner Production*, 169:161-177. https://doi.org/10.1016/j.jclepro.2017.05.165.
Desdemoustier, J., Crutzen, N., and Giffinger, G. (2019): “Municipalities' understanding of the smart city concept: An exploratory analysis in Belgium”, *Technological Forecasting and Social Change*, **142**: 129-141. https://doi.org/10.1016/j.techfore.2018.10.029
Elgazzar, R., and El-Gazzar, R. (2017): “Smart cities, sustainable cities, or both? - A critical review and synthesis of success and failure factors”, in *Proceedings of the 6th International Conference on Smart Cities and Green ICT Systems*, Volume 1: 250-257. https://doi.org/10.5220/0006307302500257
Estevez, E., Lopes, N., and Janowski, T. (2016): *Smart sustainable cities: Reconnaissance study*, United Nations University, UNU-EGOV Reports.
https://collections.unu.edu/view/UNU:5825#viewAttachments
Esposito, G., Clement, J., Mora, L. and Crutzen, N. (2021): “One size does not fit all: Framing smart city policy narratives within regional socio-economic contexts in Brussels and Wallonia”, *Cities*, **118**: 103329. https://doi.org/10.1016/j.cities.2021.103329.
European Commission (2012): *Communication from the commission. Smart cities and communities – European innovation partnership.*
http://ec.europa.eu/energy/technology/initiatives/doc/2012_4701_smart_cities_en.pdf
Haarstad, H. (2017): “Constructing the sustainable city: Examining the role of sustainability in the ‘smart city’ discourse”, *Journal of Environmental Policy & Planning*, **19**: 423-437.
https://doi.org/10.1080/1523908X.2016.1245610
Hawkins, C.V., Krause, R., Feiock, R.C. and Curley, C. (2016): “Making meaningful commitments: Accounting for variation in cities’ investments of staff and fiscal resources to sustainability”, *Urban Studies*, **53**: 1902-1924.
https://doi.org/10.1177/0042098015580898
Krause, R. (2012a): “An assessment of the impact that participation in local climate networks has on cities’ implementation of climate, energy, and transportation policies”, *Review of Policy Research*, **29**: 585-604.
https://doi.org/10.1111/j.1541-1338.2012.00582.x
Krause, R. (2012a): “Political Decision-making and the local provision of public goods: The case of municipal climate protection in the US”, *Urban Studies*, **49**: 2399-2417.
https://doi.org/10.1177/0042098011427183
Hultman, N.E., Clarke, L., Frisch, C. *et al.* (2020): “Fusing subnational with national climate action is central to decarbonization: the case of the United States”, *Nature Communications*, **11**: 5255. https://doi.org/10.1038/s41467-020-18903-w

Hsu, A., Höhne, N., Kuramochi, T. *et al.* (2019): "A research roadmap for quantifying non-state and subnational climate mitigation action", *Nature Climate Change,* **9**: 11-17. https://doi.org/10.1038/s41558-018-0338-z

Hsu, A., Tan, J., Ng, Y.M., Toh, W., Vanda, R., and Goyal, N. (2020): "Performance determinants show European cities are delivering on climate mitigation", *Nature Climate Change*, **10**: 1015-1022. https://doi.org/10.1038/s41558-020-0879-9

de Jong, M., Joss, S., Schraven, D., Zhan, C., and Weijnen, M. (2015): "Sustainable–smart–resilient–low carbon–eco–knowledge cities: Making sense of a multitude of concepts promoting sustainable urbanization", *Journal of Cleaner Production*, **109**: 25-38. https://doi.org/10.1016/j.jclepro.2015.02.004

Kennedy, C., Demoullin, S., and Mohareb, E. (2012): "Cities reducing their greenhouse gas emissions," *Energy Policy*, **49**: 774-777. https://doi.org/10.1016/j.enpol.2012.07.030

Kennedy, C., Ibrahim, N. and Hoornweg, D. (2014): "Low-carbon infrastructure strategies for cities" *Nature Climate Change*, **4**: 343-346. https://doi.org/10.1038/nclimate2160

Khan, F., and Sovacool, B.K. (2016) "Testing the efficacy of voluntary urban greenhouse gas emissions inventories", *Climatic Change*, **139**: 141-154. https://doi.org/10.1007/s10584-016-1793-z

Kramers, A., Höjer, M., Lövehagen, N., and Wangel, J. (2014): "Smart sustainable cities - Exploring ICT solutions for reduced energy use in cities", *Environmental Modelling & Software*, **56**: 52-62. https://doi.org/10.1016/j.envsoft.2013.12.019

Kummitha, R.K.R., and Crutzen, N. (2017): "How do we understand smart cities? An evolutionary perspective", *Cities* **67**: 43-52. https://doi.org/10.1016/j.cities.2017.04.010

Lombardi, P., Giordano, S., Farouh, H., and Yousef, W. (2012): "Modelling the smart city performance", *Innovation*, **25**: 137-149. https://doi.org/10.1080/13511610.2012.660325

Lee, J.H., Gong Hancock, M., and Hu, M.C. (2014): "Towards an effective framework for building smart cities: Lessons from Seoul and San Francisco", *Technological Forecasting and Social Change,* **89**: 80-99. https://doi.org/10.1016/j.techfore.2013.08.033.

Manville, C., Cochrane, G., Cave, J., Millard, J., Pederson, J.K., Thaarup, R.K., Liebe, A., Wissner, M., Massink, R., and Kotterink, B. (2014): *Mapping smart cities in the EU*, Directorate General for Internal Policies, European Parliament. https://op.europa.eu/en/publication-detail/-/publication/78882e80-fc4a-4a86-9c39-2ad88ab89f9b

Martin, C., Evans, J., and Karvonen, A. (2018): "Smart and sustainable? Five tensions in the visions and practices of the smart-sustainable city in Europe and the US", *Technological Forecasting and Social Change*, **133**: 269-278. https://doi.org/10.1016/j.techfore.2018.01.005

Nam, T., and Pardo, T.A. (2011): "Conceptualizing smart city with dimensions of technology, people, and institutions", *Proceedings of the 12th Annual International Digital Government Research Conference: Digital Government Innovation in Challenging Times*: 282-291.

Neirotti, P., De Marco, A., Cagliano, A.C., Mangano, G., and Scorrano, F. (2014): "Current trends in smart city initiatives: Some stylised facts", *Cities*, **38**: 25-36.
https://doi.org/10.1016/j.cities.2013.12.010

Noori, N., de Jong, M., Janssen, M., Schraven, D., and Hoppe, T. (2020): "Input-output modeling for smart city development", *Journal of Urban Technology, forthcoming.*
https://doi.org/10.1080/10630732.2020.1794728

Prado-Lorenzo, J.M., García-Sánchez, I.M., and Cuadrado-Ballesteros, B. (2012) "Sustainable cities: Do political factors determine the quality of life?", *Journal of Cleaner Production*, **21**: 34-44.
https://doi.org/10.1016/j.jclepro.2011.08.021.

Saha, D. (2009): "Factors influencing local government sustainability efforts", *State and Local Government Review*, **41**: 39-48. https://doi.org/10.1177/0160323X0904100105

Shapira, P., Gök, A., Klochikhin, E., and Sensier, M. (2014): "Probing 'green' industry enterprises in the UK: A new identification approach", *Technological Forecasting and Social Change*, **85**: 93-104.
https://doi.org/10.1016/j.techfore.2013.10.023

Steffen, B., Schmidt, T.S., and Tautorat, P. (2019): "Measuring whether municipal climate networks make a difference: The case of utility-scale solar PV investment in large global cities", *Climate Policy*, 19: 908-922. https://doi.org/10.1080/14693062.2019.1599804

Trindade, E.P., Hinnig, M.P.F., da Costa, E.M., Sabatini Marques, J., Cid Bastos, R., and Yigitcanlar, T. (2017): "Sustainable development of smart cities: A systematic review of the literature", *Journal of Open Innovation*, **3**: 1-14. https://doi.org/10.1186/s40852-017-0063-2

Yigitcanlar, T., and Kamruzzaman, Md. (2018): "Does smart city policy lead to sustainability of cities?", *Land Use Policy*, **73**: 49-58. https://doi.org/10.1016/j.landusepol.2018.01.034

Yigitcanlar, T. and Kamruzzaman, Md., Foth, M., Sabatini-Marques, J., da Costa, E., Ioppolo, G. (2019): "Can cities become smart without being sustainable? A systematic review of the literature", *Sustainable Cities and Society*, **45**:348-365. https://doi.org/10.1016/j.scs.2018.11.033

Wang, R. (2012): "Adopting local climate policies: What have California cities Done and why?", *Urban Affairs Review*, **49**: 593-613.
https://doi.org/10.1177/1078087412469348

Wang, X., Hawkins, C.V., Lebredo, N. and Berman, E.M. (2012): "Capacity to Sustain Sustainability: A Study of U.S. Cities", *Public Administration Review*, **72**: 841-853.
https://doi.org/10.1111/j.1540-6210.2012.02566.x

Washburn, D., and Sindhu, U. (2010): *Helping CIOs understand "smart city" initiatives*: *Defining the smart city, its drivers, and the role of the CIO*, Forrester Research, February. https://www.forrester.com/report/Helping+CIOs+Understand+Smart+City+Initiatives/-/E-RES55590

Wooldridge, J.M. (2010): *Econometric analysis of cross section and panel data*, MIT Press, 2nd edition.

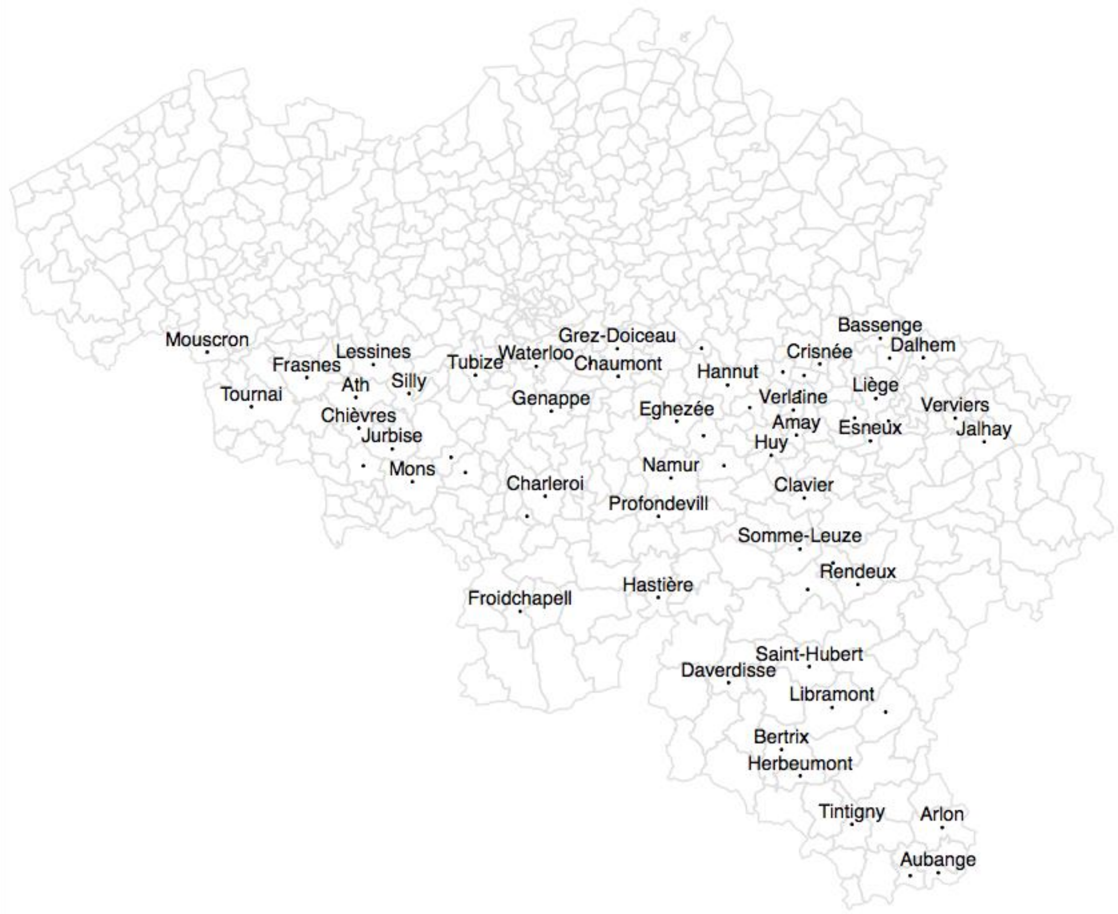
Zahran, S., Grover, H., Brody, S.D. and Vedlitz, A. (2008a): "Risk, stress, and capacity: Explaining metropolitan commitment to climate protection", *Urban Affairs Review*, **43**:447-474.

https://doi.org/10.1177/1078087407304688

Zahran, S., Grover, H., Brody, S.D., Vedlitz, A., and Miller, C. (2008b): “Vulnerability and capacity: explaining local commitment to climate-change policy”, *Environment and Planning C: Government and Policy*, **26**: 544-562. https://doi.org/10.1068/c2g

Zeppel H. (2013): “The ICLEI Cities for Climate Protection Programme: Local government networks in urban climate governance”, in Cadman T. (eds), *Climate Change and Global Policy Regimes. International Political Economy,* Palgrave Macmillan. https://doi.org/10.1057/9781137006127_15

Figure 1: Sample of Wallonian municipalities.



Note: The dots in the map indicate the municipalities in the sample.

Table 1: Summary statistics

	Obs.	*Mean*	*St. Dev.*	*Min.*	*Max.*	*Source*
Panel A: Dependent Variables						
Air quality index (2015-2017)	262	0.00	0.42	–0.97	0.88	Agence Wallone de l'air & du climat
Air quality index (2017-2019)	262	0.00	0.38	–0.90	0.79	Agence Wallone de l'air & du climat
Smart city orientation: Sustainable	61	0.15	0.36	0	1	Smart City Survey (Bounazef *et al.* 2018)
Smart city orientation: Digital	61	0.16	0.36	0	1	Smart City Survey (Bounazef *et al.* 2018)
Smart city orientation: Digital & Sustainable (D&S)	61	0.43	0.50	0	1	Smart City Survey (Bounazef *et al.* 2018)
Smart city orientation: Neither/nor D&S	61	0.23	0.44	0	1	Smart City Survey (Bounazef *et al.* 2018)
Panel B: Control Variables						
Smart city (participation in regional programme dummy)	262	0.37	0.48	0.00	1.00	Digital Wallonia
Smart city (level of implementation)	61	3.72	2.35	0.00	9.00	Smart City Survey (Bounazef *et al.* 2018)
Share of woodland (%)	262	23.24	20.29	0.00	76.16	Belfius (2007, 2017)
Density (thousand people)	262	0.32	0.44	0.03	3.50	Belfius (2007, 2017)
$Income_{pc}$ (euros per thousand people)	262	17.33	2.13	11.82	25.04	Belfius (2007, 2017)
Population (in thousands)	262	13.80	21.12	1.43	201.26	Statbel, Statistics Belgium
Emissions Trend (Air quality index 2012-2014 minus Air quality index 2012-2010)	262	0.00	0.13	–0.37	0.27	Agence Wallone de l'air & du climat and own calculations
Share of Past Environmental Programmes in Wallonia (%)	262	55.23	17.43	10	100	Service public de Wallonie
Air quality index (2014-2016)	262	0.00	0.37	–0.84	0.93	Agence Wallone de l'air & du climat
Rainfall (average 1991-2020, log of mm of liquid water equivalent)	61	6.80	0.14	6.57	7.15	Institut royal météorologique
# Vehicles per household	262	1.22	0.13	0.74	1.68	Belfius (2007, 2017)
# kms. of motorways (in thousands)	262	0.03	0.02	0.00	0.18	Belfius (2007, 2017)
Share of green firms (%)	262	15.84	3.81	9.05	26.88	Bureau van Dijk and own calculations (Shapira *et al.* 2014)
Share of population with a university degree (%)	262	6.04	3.51	1.47	22.50	Belfius (2007, 2017)
Share of seats of winning party (local elections 2018)	262	58.83	15.38	28	100	Service public de Wallonie
# parties (local elections 2018)	262	7.03	2.75	3.00	23.00	Service public de Wallonie
Unemployment rate (%)	262	9.31	3.12	3.36	19.93	Belfius (2007, 2017)
Median stakeholders' involvement	61	2.61	1.66	0.00	4.00	Smart City Survey (Bounazef *et al.* 2018)

Note: Complete definitions and details on the statistical sources of the variables can be found in Section 3.

Table 2: Effectiveness of SSCs (OLS estimates, Air quality index)

	Air quality index (2015-2017) (i)	Air quality index (2015-2017) (ii)	Air quality index (2017-2019) (iii)	Air quality index (2017-2019) (iv)	Air quality index (2017-2019) (v)	Air quality index (2017-2019) (vi)	Air quality index (2017-2019) (vii)
Smart city: Participation	0.0151 (0.0384)		0.0003 (0.0344)		–0.0040 (0.0349)		
Smart city: Level of Implementation		–0.0100 (0.0682)		–0.0088 (0.0154)		–0.0033 (0.0145)	
Smart city: Level of Implementation^2		0.0008 (0.0071)					
Smart city orientation (SCO): Digital							–0.1634 (0.1235)
Smart city orientation: Digital & Sustainable (D&S)							–0.0623 (0.1011)
Smart city orientation: Neither/nor D&S							0.0395 (0.1026)
Share of woodland	–0.0117*** (0.0010)	–0.0120*** (0.0024)	–0.0095*** (0.0009)	–0.0090*** (0.0024)	–0.0095*** (0.0010)	–0.0090*** (0.0023)	–0.0099*** (0.0023)
Density	0.1768*** (0.0502)	0.1314 (0.0996)	0.1412*** (0.0507)	0.1141 (0.1700)	0.1645*** (0.0542)	0.1186 (0.1615)	0.0873 (0.1618)
Income$_{pc}$	0.0254** (0.0102)	0.0274 (0.0204)	0.0376*** (0.0104)	0.0409* (0.0221)	0.0363*** (0.0105)	0.0378* (0.0221)	0.0381 (0.0244)
Population			0.0005 (0.0008)	0.0006 (0.0020)	0.0001 (0.0008)	0.0001 (0.0020)	0.0002 (0.0024)
Emissions Trend (ET)			–0.3525* (0.1932)	–0.3652 (0.3380)	–0.1073 (0.2688)	0.7774 (0.6166)	–1.0358 (0.6435)
Past Environmental Programmes			–0.9623 (1.0475)	–0.5554 (1.8737)	–0.7301 (1.0336)	–1.4841 (1.9840)	–1.0294 (2.0620)
ET × Smart city					–0.5596* (0.2876)	–0.3063** (0.1207)	
ET × SCO Sustainable (constant term)							-0.3300 (0.4997)
ET × SCO Digital							1.1977 (0.7955)
ET × SCO D&S							0.2806 (0.9382)
ET × SCO Neither/nor D&S							1.5115** (0.7311)
Observations	262	61	262	61	262	61	61
Adj. R-squared	0.46	0.41	0.46	0.40	0.47	0.45	0.42

Note: The dependent variable in columns (i) and (ii) is the quality index for the 2015 to 2017 period, whereas the quality index for the 2017 to 2019 period is used in the rest of the columns. Definitions of the dependent and explanatory variables can be found in Section 3. A constant term was included but not reported, except in the last column. The asterisks denote statistically significant coefficients at the 1% level (***), 5% level (**) and 10% level (*). Robust standard errors in brackets.

Table 3: Drivers of SSCs (Multinomial Logit estimates, Smart City Orientation - SCO)

	SCO: Digital (i)	SCO: D&S (ii)	SCO: Neither/nor D&S (iii)	SCO: Sustainable (iv)	SCO: Digital (v)	SCO: D&S (vi)	SCO: Neither/nor D&S (vii)	SCO: Sustainable (viii)	SCO: Digital (ix)	SCO: D&S (x)	SCO: Neither/nor D&S (xi)	SCO: Sustainable (xii)
Air quality	3.2733	7.4286**	7.4769*		4.1132	8.7827	8.6416		9.9651	17.7612**	17.5510***	
index (2014-2016)	(4.1377)	(3.7193)	(4.1251)		(6.1450)	(5.4360)	(6.1544)		(6.3936)	(6.9090)	(6.6829)	
Woodland	–0.2763***	–0.2268***	–0.2296**		–0.380**	–0.2439*	–0.3118**		–0.5910***	–0.4060*	–0.5378**	
	(0.1023)	(0.0875)	(0.0953)		(0.1610)	(0.1326)	(0.1514)		(0.2102)	(0.2164)	(0.2396)	
Rainfall	20.9106	29.5409**	26.2591*		24.7180	32.1655*	32.9851		47.5558**	63.6767**	61.1613**	
	(15.9755)	(13.8806)	(14.4181)		(21.3360)	(18.3450)	(20.3555)		(23.7132)	(29.5538)	(28.8253)	
Density	–8.8412**	–7.8243***	–10.0168***		–8.1370	–9.5337**	–11.5881**		–19.5886***	–21.2375***	–20.3579***	
	(4.4598)	(2.7964)	(3.5991)		(5.9529)	(4.8581)	(5.3614)		(6.8382)	(5.8396)	(6.1802)	
# Vehicles per	–4.5567	–0.5900	–2.9384		–33.9787**	–5.1435	–15.3665		–38.8705**	1.6816	–14.3832	
household	(10.5382)	(7.9554)	(8.4884)		(16.5583)	(10.8551)	(12.7817)		(18.3177)	(13.9464)	(15.5523)	
# kms. of	–0.0077	0.0009	–0.0029		–0.0111	0.0008	–0.0044		–0.0270	–0.0122***	–0.0061	
motorways	(0.0054)	(0.0022)	(0.0046)		(0.0079)	(0.0017)	(0.0041)		(0.0171)	(0.0047)	(0.0102)	
Share of	–0.0714	–0.4820**	–0.2795		–0.0932	–0.4716	–0.4732*		–0.6572	–0.9615**	–1.0558***	
green firms	(0.2384)	(0.2712)	(0.2229)		(0.3349)	(0.2875)	(0.2657)		(0.4571)	(0.4231)	(0.4048)	
Income$_{pc}$	–3.1534***	–2.6551***	–2.6632***		–5.0152**	–3.3005*	–3.7776*		–9.0650***	–7.2460***	–8.3752***	
	(1.2061)	(0.9881)	(1.0258)		(2.0375)	(1.8348)	(1.9592)		(2.6617)	(2.7607)	(2.9001)	
Share of population	1.6390**	1.1693**	1.1295**		2.9418***	1.6429	1.7881		5.2952***	3.7053**	4.2219**	
w. university degree	(0.6607)	(0.5172)	(0.5625)		(1.1199)	(1.0302)	(1.1127)		(1.5767)	(1.5247)	(1.6668)	
Share of seats					0.0458	0.0509	0.0937		0.0705	0.0747	0.1206	
winning party					(0.0787)	(0.0610)	(0.0644)		(0.0931)	(0.0801)	(0.0781)	
# Parties					–0.8518*	–0.0045	–0.1371		–1.4902***	–0.4176	–0.3699	
					(0.4430)	(0.1722)	(0.2454)		(0.3694)	(0.4867)	(0.5207)	
Unemployment					–1.7469***	–0.0377	–0.5352**		–2.4055***	–0.5447**	–0.7137***	
					(0.6595)	(0.2048)	(0.2534)		(0.6855)	(0.2752)	(0.2024)	
Population									1.1757**	2.1021***	1.1899**	
									(0.4890)	(0.5556)	(0.5359)	
Past Environmental									0.0118	–0.0603	–0.0667	
Programmes									(0.0586)	(0.0496)	(0.0551)	
Stakeholders'									0.0858	0.1638*	–0.0886	
involvement									(0.1540)	(0.0928)	(0.1806)	
Air quality index	–0.3469*	0.4795*	0.3679	–0.5006***	–0.2456	0.5012**	0.3068	–0.5624***	–0.3070	0.6611**	0.5171**	–0.8713***
(2014-2016), AME	(0.2042)	(0.2588)	(0.3073)	(0.1713)	(0.1594)	(0.2085)	(0.2678)	(0.1995)	(0.2080)	(0.2676)	(0.2425)	(0.2704)
Wald Test	53.73***				106.17***				468.95***			
McFadden's pseudo R-squared	0.29				0.43				0.56			

Note: The dependent (categorical) variable is the smart city orientation (SCO): Digital, Digital & Sustainable (D&S), and Neither Digital & Nor Sustainable (Neither/nor D&S), and Sustainable (which is the reference category). AME stands for Average Marginal Effects of Air quality on the probability of each alternative. Definitions of the dependent and explanatory variables can be found in Section 3. A constant term was included but not reported. Wald Test is the χ^2-joint significant test. The asterisks denote statistically significant coefficients at the 1% level (***), 5% level (**) and 10% level (*). Robust standard errors in brackets. The number of observations is 61 (all columns).