Smart Cities and urban inequality[1]

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Abstract

Smart City technologies are criticized as they might exacerbate income inequalities. Four factors are suggested for explaining this phenomenon: the uneven diffusion of ICTs, these technologies cannot be afforded by low-income citizens, Smart Cities could further human capital divides, and the involvement of private actors in the implementation of projects.

These critiques are not based on empirical verification. We test whether smart urban characteristics are associated with increases in urban income inequalities, using data on urban smartness and urban income inequality for106 European cities. Results show that Smart Cities are associated with lower levels of urban income inequality.

Keywords: Smart cities; Urban Inequality; Digital divide; Income distribution.

JEL classification codes: R11, D63, J24

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Introduction

Smart Cities are on the agenda of many city officials worldwide; they are the object of countless innovative projects by leading high-tech companies; and, consequently, they are being studied by scholars in different disciplines. The success of this concept goes well beyond the walls of the academia and has attracted large funding from public bodies both in urban areas aiming at strengthening their technological platforms (Osborne, 2017) as well as from governments interested in founding tech-savvy cities from scratch (Sharma, 2019).

However, the Smart City planning paradigm is also eyed with suspicion considering its alleged role in increasing inequalities. For instance, an article in The Guardian entitled "*The truth about smart cities: In the end, they will destroy democracy*" (Poole, 2014) lists several strong arguments against the possibly unequal and anti-democratic effects that the pervasive diffusion of personal devices, coupled with the conferment of data thereby collected to private companies, may cause. For the sake of our work, a more specific critique against the potentially uneven impact of the diffusion of smart technologies in cities is presented in Kharas and Remes (2018), who suggest several possible examples of the channels through which income inequality may be spurred in Smart Cities, concluding nevertheless that whether this negative dystopia will actually take place really depends on the way in which urban smartness will be actually implemented.

Quantitative research measuring the extent of urban smartness and its implications for economic outcomes is scant, making it difficult to understand the relationship between smartness and inequality. Critics of the Smart City concept often ground their concerns in claiming that promoting urban smartness means increasing and exacerbating urban income inequality, mainly because of the involvement of large information communication technology (ICT) corporations providing municipalities with the technical solutions for the functioning of Smart City projects (for a general overview see e.g. Shelton et al., 2015; Kitchin et al., 2019 and Lee et al. (2020) and Section 2.2 below highlighting in detail the literature examining the negative impact of Smart Cities on inequalities). However, aside from anecdotal evidence and general conceptual claims, the link between urban smartness and income inequality has not been examined with rigorous empirical work. Given the relevance of the concerns voiced by several scholars, and the lack of sound empirical verifications, a gap exists in the literature which we address, taking stock of the theoretical arguments and insights provided in this stream of literature.

This paper thus provides a new understanding of the inequality implications of the Smart City paradigm, by answering the following research question:

RQ *Are Smart City characteristics associated with higher levels of urban income inequality?*

In answering this research question, our contribution to the literature is threefold. First, we use a quantitative indicator of smart urban features. This allows to assess the degree to which cities truly reach smartness goals along the lines of a comprehensive theoretical definition, which takes stock of and builds on previous definition and represents an broad view of Smart Cities (Caragliu et al., 2011; see Section 2.2). We also explore whether using other definitions used in the literature alters our main message. Second, we link this Smart City indicator to income inequality, thus allowing inference on the relative influence of urban smartness on urban income inequalities, controlling for other relevant urban features. This makes our results potentially replicable. Third, we go beyond simple correlations by means of Instrumental Variables (IV) techniques.

In order to operationalize the quantitative assessment of urban smartness, we adopt the definition suggested in Caragliu et al. (2011), where cities are identified as smart when: "*investments in human and social capital and traditional (transport) and modern (ICT) communication infrastructure fuel sustainable economic growth and a high quality of life, with a wise management of natural resources, through participatory governance*".

All in all, our empirical results suggest that, contrary to a widely held belief, Smart Cities tend to be characterized by lower levels of income inequalities. Results hold both using standard measures of the latter (Gini Index) as well with the use of indices capturing the welfare preferences for inequality levels at the different layers of the income distribution.

The paper is organized as follows. In Section 2 we review the main reference literature, grounding our research question in extant contributions. Section 3 presents the data base collected for this study and the indicators used in the empirical analyses. Section 4 presents the empirical results of our analyses, while Section 5 concludes with some fundamental message of policy that can be drawn from our findings.

Are Smart Cities more unequal?

Our work draws from three main strands of literature. The first comprises works that examine the determinants of income inequality at the national level; for reasons of space limitations, this angle is presented in Technical Appendix A.1. The second consists of research focusing on local (urban) determinants of income inequality. The third summarizes instead arguments in favor and against the inequality-enhancing role of smart city characteristics.

Income inequalities at the city level

While robust empirical evidence is available on the Country-level determinants of income inequalities, relatively fewer works focus on the regional and urban levels. At the national level, aggregate macroeconomic conditions, including the level of development, and structural characteristics, including institutional factors, are important correlates of income inequality (see the Technical Appendix for more details). Among the relatively scarcer contributions at the local level, a first-hand baseline classification of the extant literature can be based on aggregating works depending on whether urban and regional income inequality are considered as outcomes or as determinants of economic performance. For reasons of space limitations, we focus here on the former, and we leave the latter for a more extensive discussion in the Technical Appendix.

A recent review discussed in Marchand et al. (2020) provides extensive quantitative evidence on the regional and urban determinants of income inequalities, identified in differences in the level of economic development, in the precariousness of labor market conditions, in segregation patterns, and in socioeconomic factors. With US city-level data, Glaeser et al. (2009) and Florida and Mellander (2016) examine the determinants of income inequality. Glaeser et al. (2009) find that urban income inequality is mainly driven by the skill level of workers in the city, while Florida and Mellander (2016) show how wage inequality impacts income inequality, along with race, poverty and unionization levels. Both these contributions stress the importance of personal characteristics, especially those related to the labor market. These findings are also confirmed for European cities, as documented by Lee et al. (2016), who consider wage inequality (which in turn drives income inequality) in UK cities and find that one of the main drivers lies in the underlying distribution of skills across workers.

An additional channel for income inequalities to be related to space-specific characteristics is empirically assessed in Lee and Rodríguez-Pose (2013), who identify in higher innovation rates at the local level a potential cause for income inequalities to increase, at least in the European case; this evidence is also supported for the Canadian case in Breau et al. (2014).

Silva and Leichenko (2004) show that different US census regions react differently to a higher exposure to international trade. Moreover, Korpi (2008) shows that urban income inequality increases with city size, and that this relationship is in turn due to labor market diversification, human capital, migration, and demographic factors.

A theoretical contribution systematizing these determinants of inequality at the city level is provided in Behrens and Robert-Nicoud (2014) who develop a model that uses natural advantage, agglomeration economies and firm selection to explain why larger cities are more unequal than their smaller counterparts.

Among determinants of income inequality reductions, instead, the evidence strictly follows the classical Heckscher–Ohlin framework, suggesting that population movements help minimizing, if not inverting, inequality trends (Ayala et al., 2019). Decreasing population movements may reverse such trends: Ganong and Shoag (2017) explain the substantial decline in income convergence rates across US states by means of a model whereby rising land rent in high-income areas deter low-skilled migrants from in-migrating, thus ultimately causing a slow-down in income convergence. Lastly, Tammaru et al. (2020) show that across EU urban areas income inequalities are lower in North Europe, higher in South Europe, whereas in several Eastern European Countries inequality has substantially increased over the past two decades.

Moreover, higher quality of local governance should also be associated, all else being equal, with lower income inequalities (Beall et al., 2000). While this finding usually applies also to vast cross-sections of areas with different institutions, recent evidence suggests that less developed Countries would benefit less from good governance (Jindra and Vaz, 2018); a critique that does not apply to the sample here analyzed, comprising EU28 Countries.

Little evidence has so far been presented on the role of two crucial features in decreasing urban income inequality, which instead are considered in the present paper. Our empirical analyses control for urban form and urban smartness (the latter discussed in detail in the following subsection). A lively debate has in fact involved urban economists for the past three decades on whether a compact urban form, with tightly-knit buildings, and an efficient (public) urban transportation network allowing faster connections between different parts of the city, is indeed conducive to greater environmental sustainability (on the issues on smart urban growth and compact cities, see e.g. Dielman and Wegener, 2004 and Bibri et al. 2020), and ultimately to economic growth. On the one hand, some argue that the market should be left free to decide how to adjust the urban form in response to exogenous technological shocks. This is for instance the case of Brueckner and Fansler (1983, p. 487), who criticize the "*emotionally-charged indictment of sprawl*". On the other hand, empirical research has also shown that compact cities also tend to be more efficient, innovative, and productive (Hamidi and Zandiatashbar, 2019; Carlino et al., 2007; Camagni et al., 2013). A compact urban form also reduces income inequality, by making urban labor markets more closely integrated, thus enhancing job opportunities also for the lower layers of the income distribution (Burton, 2000).

Smart Cities: definitions and relation to income inequalities

Another branch of the literature that needs to be summarized here is related to the link between income inequality and the Smart City paradigm as emerging over the past decade.[i] In what follows we will suggest through which channels smartness can be related to inequalities and identify the distinctive elements of the definition of a Smart City we adopt in this paper with respect to other contributions in the literature, so as to shed theoretical light on the empirical analyses following thereafter. Before making this step, we will briefly summarize the lively debate emerging over the past decade on the very nature of urban smartness. This intermediate stage is needed in order to better motivate the choices made in the empirical section of our work.

According to a recent article, the history of Smart Cities dates back to the 1960s, and finds its roots in the first wave of diffusion of early ICTs: "*Beginning in the late 1960s and through most of the 1970s, the little-known Community Analysis Bureau used computer databases, cluster analysis, and infrared aerial photography to gather data, produce reports on neighborhood demographics and housing quality, and help direct resources to ward off blight and tackle poverty*" (Vallianatos, 2015).

Over time, several definitions of this concept have emerged, each differing in terms of the main "smart" characteristic deemed as the most relevant. While early conceptualizations revolved around ICTs as the main pillar around which a city should build its smart pathway, eventually other key factors have been considered as the characterizing feature of Smart Cities. From the “wired city” proposed initially by Dutton et al. (1987), other authors have stressed the importance of the users of ICTs and their ability to connect among each other and reap the benefits of technology, as in the “intelligent city” (Komninos 2002, 2006 and 2009; Deakin and Waer, 2011). Environmental aspects are instead the focus of another stream of definitions revolving around the idea of smartness as the ability to invest in technologies and implement policies aimed at increasing urban sustainability, following the notion of “resilient cities” proposed initially by Newman et al., 2009.

More recent contributions shifted the weight towards a more comprehensive approach, aimed at encompassing several key features of smartness in comprehensive definitions (Caragliu and Del Bo, 2020). The contributions in this strand of literature see Smart Cities as the unique meeting place of ICTs on the one hand, and human and social capital, bottom-up governance, and quality of life and sustainability on the other. This approach follows the seminal work by Giffinger et al. (2007), and suggests that Smart Cities exist as the result of the interplay between both tangible and intangible factors, offering an urban environment more prone to enhance the positive effects stemming from the presence of communication infrastructure. This novel characterization of Smart Cities moves beyond the focus on a single, leading factor that defines smartness, and offer a comprehensive and all-encompassing definition of the main features that define smartness (Batty et al., 2012).

This approach, in our opinion, offers several advantages. First, it encompasses several drivers of smartness that have been identified individually in the literature and in other definitions while not focusing the attention only on one. In this sense, the definition used in this paper follows the one provided by Caragliu et al. (2011) and merges several different strands of classification of what a Smart City truly is, thus avoiding to narrowly focus on just one, or few, of them. Second, it can be related to an urban production function approach, clearly distinguishing between inputs and output. Finally, it can be empirically implemented and is amenable of statistical measuring and analysis.

The distinction between ICT-oriented only, or holistic Smart Cities, has also important normative implications; in fact, a policy could be legitimately defined as a Smart City-oriented one when, for instance, funding broadband diffusion only within the first framework, while the lack of support to context conditions would exclude such policies from belonging to truly smart ones when a more comprehensive definition following the Giffinger et al. (2007) and Caragliu et al. (2011) paradigm is adopted.

While initial critiques against the notion of Smart City focused on the fuzziness of this concept (Hollands, 2008), the diffusion of successful and clear definitions quickly made this first point less relevant, while leaving room for a second generation of criticisms, increasingly dealing with the unequal nature of the benefits accruing to Smart Citizens. The microfoundations behind Smart City income inequality effects can be in particular be related to four conceptual arguments.

The first reason for Smart Cities to be potentially associated with higher levels of income inequality is based on the uneven diffusion of ICTs in cities, and, in particular, of the skills needed to fully reap the benefits of these technologies. While this channel is in principle relevant, there is to date scant evidence in support for this concern. Richmond and Triplett (2018) provide weak evidence of the former hypothesis, showing that, on the basis of a panel of country data, differential access to ICTs and skill premia seem to cause income inequality increases only for specific types of ICTs and conditionally on other local institutional factors.

Secondly, the conceptual link between smartness and income inequalities at the urban level can be understood as a consequence of adopting technologies that cannot be afforded and exploited by low-income citizens, thus leading to the worsening of inequalities. Since income inequality has an inherently spatial nature (Ayala et al., 2019) this prompts us to link this to urban smartness, which is another space-varying factor. In detail, some of the Smart solutions might be difficult to access by some segments of the population (mainly identified by the lower income segment of the population), thus further widening the gap between the wealthy and the lower-income population. This potential channel may become even stronger if smartness is identified only by its technological component and by the involvement of private actors, as posited by some scholars (Partridge, 2004). To the best of our knowledge, there is no literature examining this channel empirically.

Thirdly, investment in Smart Cities could also further the income and human capital divides already affecting several developed countries (Glaeser and Berry, 2006), since spatial differences in ICT endowment and skills can be so severe that lock-ins can derive. This argument suggests that Smart Cities may be associated with higher levels of poverty (Kummitha and Crutzen, 2017). While evidence on this last point is rather scattered, Hollands (2008) does provide qualitative proof that in cities acting as early adopters of Smart City technologies such as San Diego and Singapore poverty levels have been on the rise for decades.

Lastly, within the burgeoning literature on Smart Cities, a set of analyses highlighting the potential risks and pitfalls of the concept has emerged, mainly related to the significant involvement of private actors in the implementation of policies and projects. As an example, Hollands (2015) suggests that the Smart City concept is ultimately a corporate-driven construct, aimed at maximizing profits and returns for the firms providing municipalities with the needed ICT technologies and not conducive to welfare improvements for the citizens involved in the process. Recently, Lam and Ma (2018) have shown how negative side-effects of the Smart City developments are related to information insecurity, personal privacy leakage, information islands, and digital divide.

To sum up, an indirect argument in favor of the role of urban smartness as a factor causing further income inequalities is proposed in Vanolo (2014), who argues that the theoretical paradigms underpinning the Smart City movement are "*powerful devices to activate and rethink specific rationalities in order to justify political choices and trigger new economic paradigms—in other words, accumulation regimes that generate new businesses and possible capital accumulation*" (Vanolo, 2014, pp. 885–886).

In much of the literature so far summarized, the perverse link between Smart City technologies and income inequalities becomes stronger for Smart City projects carried out on new, artificially created cities. In fact, in the European context, urban Smart City projects can be, at least in part and alongside local public actors and private firms, financed with EU funds (Núñez Ferrer et al., 2013; Caragliu and Del Bo, 2018) and usually refer to investments in already existing cities. In other regions, instead, both the conceptual definition and the means of financing of Smart Cities might take on different meanings, suggesting that our results should be properly framed in the appropriate institutional context. In the North American and Asian context, the relative weight of the private actors with respect to public authorities is higher than in the European case (Neirotti et al., 2014), while the difference with the Arab region is that Smart City projects more often than in Europe refer to greenfield projects of newly established cities (Kitchin, 2015).

Against many of these arguments, it is important to stress that the definition of Smart Cities adopted in this paper follows Caragliu et al. (2011) and other comprehensive approaches highlighted above and thus differs from how some other scholars understand and interpret the Smart City concept, presenting a partial view of smartness. In our analysis, we focus on the smart characteristics that define a Smart City, thus going beyond the cities' own definition of their level of smartness (such as in several widely cited Smart City rankings, for instance the IESE (University of Navarra's Business School) Cities in Motion Index; see IESE, 2019) and overcoming the limits of considering a city as smart only if it is providing, possibly in partnership with a private ICT firm (Allwinkle and Cruickshank, 2011), digital solutions.

Our approach is instead inspired by an urban production function approach. With a clear distinction between inputs and outputs, smartness is an intermediate step towards the goal of smart urban growth. We refer to the comprehensive and operational definition provided in Caragliu et al. (2011), where cities are identified as smart when: "*investments in human and social capital and traditional (transport) and modern (ICT) communication infrastructure fuel sustainable economic growth and a high quality of life, with a wise management of natural resources, through participatory governance*".

Thus, while we do acknowledge the importance of the ICT component, we do not believe this is the main defining element of smartness. We address this issue in the empirical section by singling out the ICT component and using it to measure urban smartness.

The literature summarized in Section 2.2 hints at many possible rationales for the existence of a negative link between urban smartness and income inequality. This proposition will be subject to a rigorous empirical test in Section 4. Before we test this hypothesis, Section 3 will describe the main methodological details of our analyses.

Data and indicators

We now describe the methodological issues needed to translate the research question presented in Section 1 into an empirically testable model. Data and indicators are classified according to whether they are used as explanatory or dependent variables, the type of indicators, the sources of their respective raw data, the periods when they are measured, and the formula (if applicable) used to compute their values, in Table 1 below.

Typology	Indicator	Source of raw data	Period measured	Formula/Methodology
Dependent variable	Gini Index	European Value Study	2017	$I_{Gini} = \frac{1}{2\mu(F)} \iint \lvert x - x' \rvert dF(x)\, dF(x')$
Dependent variable	Generalized Entropy class Index	European Value Study	2017	$I_{GE}^{\alpha} = \frac{1}{\alpha^2 - \alpha} \int \left[\left[\frac{x}{\mu(F)} \right]^{\alpha} - 1 \right] dF(x)$
Dependent variable	Atkinson class Index	European Value Study	2017	$I_{A}^{\varepsilon} = 1 - \frac{1}{\mu(F)} \left[\int x^{1-\varepsilon} dF(x) \right]^{\frac{1}{1-\varepsilon}}$
Independent variable	Urban smartness	European Value Study/EUROSTAT	2008-2012	See Table 2
Independent variable	Real GDP	EUROSTAT	Average 1995-2010	GDP in constant market prices (base year=2010)
Independent variable	Population density	EUROSTAT	Average 1995-2010	Urban area population/ Area in sq. kms.
Independent variable	Trust	European Value Study	2009-2010	% of respondents "Most people can be trusted" to the question "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?"
Independent variable	Quality of government	Charron et al. (2014)	2010	Principal Component Analysis
Independent variable	Urban sustainability	EUROSTAT	2008-2012	Unweighted mean

Table 1. Data and indicators for the empirical analyses

Source: Authors' elaboration

Data cover the closest functional definition of an urban area proper. Within the framework of a lack of a unified and comparable set of data covering EU metropolitan areas, EUROSTAT has recently proposed the use of European NUTS3 regions (and their combinations) to proxy for functional urban areas (FUAs). FUAs comprise "*a densely inhabited city and a less densely populated commuting zone whose labour market is highly integrated with the city*" (EUROSTAT, 2020). When this is not possible, we opt for the territorially closest administrative definition.[ii] For the sake of our work, a choice of spatial units based on a functional classification has many perks, in that the externalities generated by smart urban characteristics do not obey administrative boundaries.

Our three main dependent variables are among the most commonly used indicators of income inequality. Following Cowell (2000) and Mac Gregor et al. (2019), we provide a brief sketch of the analytical formulation of the three families of indices to measure income inequality.[iii]

First, we consider the Gini index, which is computed as the normalized average absolute difference between all pairs of incomes in the underlying population. This is a widely used index, its appeal being due also to its graphical interpretation as the area between the Lorenz curve, which provides a representation of the distribution of wealth, and the 45° line in the plane where the y-axis is the proportion of income and the x-axis is the proportion of the population.

Defining X_i as the cumulative income of individual i and Y_i the cumulative population up to individual i, the Gini index can be expressed, in discrete form and based on sorted values as prepared visually for a Lorenz curve, as (Eq. 1):

$$I_{Gini} = 1 - \sum_{i=1}^{N} (X_i - X_{i-1})(Y_i - Y_{i-1}) \tag{1.}$$

Income inequality data are mostly calculated at the NUTS3 level (2013 classification), whenever information on the location of respondents at this level is available in the most recent version of the European Value Study (2017).[iv] When georeferentiation at NUTS3 level is not available, we integrate data with NUTS2 level ones. The unit of observation is the household of the survey interviewee.

The empirical analysis is carried out in two steps. In the first step, we exploit a Mincerian approach to explain individual income levels by controlling for individual characteristics. The predicted values of this first-stage regression are then used to calculate average urban income levels to be used in the second step.[v]

The main explanatory variable, which provides for an empirical test of the main research question, is urban smartness. We follow the work presented in Caragliu and Del Bo (2015, 2018, 2019) by calculating an average city-level indicator of smartness. This is obtained by combining, through an unweighted mean, unique indicators for each of the six axes of the definition provided in Caragliu et al. (2011) (*human capital; social capital; transport infrastructure; ICTs; natural resources; e-government*; see Section 2 above). The latter are obtained as a Principal Component Analysis (PCA) of indicators for the 4/5 vectors per axis shown in Table 2. In other words, PCAs are first performed on each vector measuring the intensity of endowment of the six axes, and the resulting first components (by calculation normally distributed, and centered around zero) are then averaged out.

Data on urban smartness cover an overall sample of 106 EU cities; explanatory vectors include data ranging between 2008 and 2012.

Urban smartness axis	Raw data
1. Human capital	Proportion of population aged 15-64 qualified at tertiary level (ISCED 5-6) living in Urban Audit cities - %
	Students in tertiary education (ISCED 5-6) living in Urban Audit cities - number of students per ,1000 inhabitants
	Proportion of employment in financial intermediation business activities
	Proportion of employment public administration health education
	Number of companies with headquarters in the city quoted on the national stock market
2. Social capital	Car thefts per 1,000 pop.
	Burglaries per 1,000 pop.
	Crimes per 1,000 pop.
	Number of elected city representatives
3. Transport infrastructure	Length of public transport network per inhabitant
	Share of restricted bus lanes from public transport network
	Number of buses (or bus equivalents) operating in the public transport per 1,000 pop
	Number of stops of public transport per 1,000 pop.
4. ICT infrastructure	Percentage of families with internet access at home
	Number of local units producing ICT products
	Number of local units producing ICT-related services
	Number of local units producing web content
5. Natural resources	Proportion of solid waste arising within the boundary processed by recycling
	Proportion of the area in green space
	Green space (in m2) to which the public has access, per capita
	Annual average concentration of PM_{10}
	Annual average concentration of NO_2
6. E-government	% of internet users who interacted via internet with the public authorities in the last 12 months (Country data)
	% of internet users who sent filled forms to public authorities in the last 12 months (Country data)
	Number of administrative forms available for download from official web site
	Number of administrative forms which can be submitted electronically

Table 2. Indicators for the 6 axes of the Smart City definition
Source: Caragliu and Del Bo (2015)

As for other control variables, following the discussion of the literature on determinants of inequality presented in Section 2, we include data on urban real GDP, population density, trust, and quality of government.

Urban real GDP is calculated at the NUTS3 level by deflating nominal GDP levels (averaged out for the period 1995-2010 in order to smooth business cycles as well as the territorially heterogeneous impact of the 2007/2008 financial crisis) with national price deflators. Data are expressed in constant 2010 Euros.

Population density is measured by the ratio of NUTS3 population to NUTS3 area in squared kilometers, again averaged out between 1995 and 2010 to smooth medium run demographic trends.

-Trust represents a proxy for general social capital effects. This indicator is based on the 1999-2000 edition of the European Values Study, and is calculated as the percentage of respondents "*Most people can be trusted*" to the question "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?".

In the absence of urban data comparable across the whole Europe, Quality of Government is calculated on the basis of the 2010 version of the European Quality of Government Index (EQI) described in Charron et al. (2014). The EQI represents a composite indicator calculated at NUTS2 level comprising sub-indicators of low corruption, rule of law, bureaucratic effectiveness, government voice and accountability, and strength of democratic and electoral institutions. Data are collected at NUTS2 level, and the value of each NUTS2 region is attributed to the metropolitan (NUTS3) area within each NUTS2 region.

Lastly, in order to rule out the possibility that urban smartness truly captures only the effect of sustainable urban management,[vi] we calculated a city-specific index of urban sustainability, as an unweighted mean of three indicators, measuring respectively cities' exposure to the risk of poverty, to environmental degradation, and to energy inefficiency. These are calculated, respectively, as people at risk of poverty or social exclusion; per capita municipal waste; and the number of cooling and heating degree days. All data are collected from various EUROSTAT raw sources[vii].

Many of the above-mentioned indicators could be affected by serial correlation (Bettencourt et al., 2007), mainly driven by the scaling properties underlying most of them. In order to deal with this potential issue, we provide (in a separate Technical Appendix, also showing the main descriptive statistics for these indicators, Table A.2) additional details on the correlation structure among these factors. While the interested reader is referred to the appendix for a full-fledged comment, it is worth mentioning that variables tend to behave normally, with symmetric distributions and light tails, except for the income inequality measures, which instead reflect a remarkable spatial heterogeneity.

Our empirical analyses are thus based on the following model (Eq. 2):

$$\mathrm{INEQ}_{c,t} = \alpha + \beta \mathrm{smartness}_{c,t-1} + \beta \mathrm{Z}_{c,t-1} + \varepsilon_{c,t} \qquad (2.)$$

where INEQ is our measure of inequality (calculated with the Gini, entropy, and Atkinson indexes, respectively); smartness is a measure of our definition; and Z is a matrix of controls including all variables described in Table 1. Indices c and t indicate city c and time t, respectively; and, lastly, $\varepsilon_{c,t}$ is an i.i.d. disturbance error.

Eq. (2.) will be estimated by means of Ordinary Least Squares (OLS, Table 3 and Table 4, columns 1-4; 6-9), Two Stages Least Squares (2SLS, Table 4, Column 10) and Maximum Likelihood of a Spatial Durbin Model (Table 4, column 5).

Empirical results

This section presents and discusses the empirical estimates answering the research question proposed in Section 1. We proceed as follows. In Section 4.1 we present the baseline model where the dependent variable is a Gini Index of income inequality. The assumption behind the use of this indicator is that the citizenship is neutral w.r.t. income distribution for different income brackets. Then, in Section 4.2 we deal with identification issues first by running a number of additional robustness checks to verify whether our results suffer from possible omitted variable bias, and then by resorting to a classical Instrumental Variable Strategy.[viii]

Baseline estimates

Estimates of the baseline model are presented in Table 3. All estimates are based on heteroscedasticity-robust standard errors.

Table 3 is organized as follows. In each column we present a different model, each of which includes an additional regressor, in order to highlight possible multicollinearity issues. We start from a baseline regression linking urban smartness to income inequality (Column 1), and then add urban GDP (Column 2), replace the latter with population density (Column 3), include both GDP and population density (Column 4), add trust (Column 5), replace it with Quality of Government (Column 6), and, finally, include both trust and Quality of Government (Column 7).

Dependent variable: Gini index							
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Urban smartness	-0.00580***	-0.00370**	-0.00550***	-0.00384**	-0.00333**	-0.00278*	-0.00263*
	(-4.29)	(-2.40)	(-4.03)	(-2.49)	(-2.10)	(-1.75)	(-1.67)
Log real GDP		-0.00739**		-0.00618	-0.00242	-0.000321	0.00102
		(-2.14)		(-1.62)	(-0.61)	(-0.08)	(0.25)
Log population density			-0.00312*	-0.00215	-0.00297	-0.00257	-0.00297*
			(-1.84)	(-1.18)	(-1.61)	(-1.57)	(-1.69)
Trust					-0.0285**		-0.0155
					(-2.02)		(-0.98)
Quality of government						-0.000333***	-0.000293**
						(-3.07)	(-2.45)
Constant	0.104***	0.176***	0.121***	0.176***	0.153***	0.142***	0.134***
	(52.91)	(5.19)	(12.79)	(5.15)	(4.59)	(4.23)	(3.97)
Observations	106	106	106	106	106	106	106
Largest VIF	1	1.27	1.02	1.53	2.17	2.15	2.47
Adjusted R^2	0.128	0.164	0.148	0.169	0.187	0.223	0.222

Table 3. Baseline model estimates

*Note: t-statistics in parentheses. *: 0.10: significance level. **: 0.05 significance level. ***: 0.01 significance level.*

The crucial estimate here is the coefficient associated to urban smartness. This turns out to be significantly different from zero and negatively associated with income inequalities, with decreasing parameter estimates and significance levels as additional controls are also included in the model. The decreasing sign of the estimated parameter as additional controls are included indirectly suggests that urban smartness as defined in this paper comprises several features making a city more efficient, within the urban smartness paradigm. Delving more into the details of the relative magnitude of this parameter, based on our preferred specification (Column 3), a 1 per cent increase in urban smartness is associated, all else being equal, to a 0.18 per cent decrease in the Gini Index of the average city. Given the distribution of values of this index in the analyzed sample, this means that moving from the city of Düsserdolf to the city of Brescia, around the mean of the smartness distribution and contiguous in terms of the urban smartness distribution, would cause a decrease of the inequality (Gini) index from 0.11 to 0.09.

The level of development, as summarized by GDP, is negatively associated with income inequality (Column 2). The same can be said for population density, suggesting a negative association between compact city structure and inequality (Column 3). As expected, GDP levels and population density turn out to be mutually correlated (Klasen and Nestmann, 2006), as testified by the crowding out effect that the inclusion of both has (Column 4) on the significance of their parameter estimates, as well as by the fact that the impact of smartness found in model 4 is slightly higher than in the case of model 2, where only GDP is included, but lower than in the case of model 3, which controls for density, and not for GDP levels.

We also find a negative association between social capital, measured by urban trust levels, and income inequality, which nevertheless becomes not significantly distinguishable from zero after controlling for the local quality of institutions. The latter are instead a strong predictor of lower levels of urban income inequality (Column 7), even after controlling for urban trust. These results are in line with the consensus, also in the literature focusing on country-level determinants, that structural characteristics and institutional factors are strongly and significantly correlated with income inequalities. A city with good institutional quality and high levels of interpersonal trust is also a city with lower level of income inequality.

All in all, using these specifications, we explain roughly 22 per cent of total variance.[ix]

Identification issues

This last subsection deals with two reasons why the main findings presented in Section 4.1 could be potentially biased:

- Omitted Variable bias;
- Reverse causality.

As for the former, one may argue that our results could be driven by the omission of other relevant factors that co-vary with our right hand side (RHS) variables, so that both independent and dependent variables in our model are simultaneously driven by these missing variables. As instead for the latter, higher scores in urban smartness may not be causing a reduction in income inequalities, despite the careful choice of timing for the variables included in the model, but rather be due to them, or, alternatively, both could be simultaneously caused by other factors. In the absence of randomized experiments, the usual choice is to resort to Instrumental Variables (Angrist and Krueger, 2001).

In order to test the robustness of our results for potential omitted variables bias, Table 4 shows the following controls. In Column 1 we show whether our results are affected by the relatively traditional definition of urban smartness we adopt, and in particular whether recently successful urban smart services could potentially affect the negative relation we identify between urban smartness and income inequality. For this reason, we also control for the presence of bike sharing services in each urban area (with a dummy variable, equal to 1 if the city offers bike sharing services, and zero otherwise). This variable turns out to be not associated with income inequality, while results for the main relationship remain unaffected.

The second control specifically tackles the issue often raised in the literature and also referred to in Section 2 above, viz. whether Urban Smartness represents a new urban policy style altogether or if instead it is its ICT component that truly drives the effects the applied literature is identifying. This control is shown in Column 2, which drops the composite smartness indicator and adds its ICT component only. The negative smartness impact is no longer statistically distinguishable from zero if only ICTs are taken into account, providing support for the hypothesis that Smart Cities are truly about the interaction between sensors and citizens.

Dependent variable: Gini coefficient										
Model	*(1.)*	*(2.)*	*(3.)*	*(4.)*	*(5.)*	*(6.)*	*(7.)*	*(8.)*	*(9.)*	*(10.)*
Urban smartness	-0.00285*		-0.00288*	-0.00248	-0.00200	-0.00271	-0.00298*	-0.00562**	-0.00269*	-0.0122***
	(-1.80)		(-1.77)	(-1.63)	(-1.20)	(-1.61)	(-1.94)	(-2.26)	(-1.67)	(-4.14)
Log real GDP	0.000485	-0.000808	0.00124	-0.00176	-0.000942	-0.000269	0.0000500	0.00610	0.00274	0.00702***
	(0.12)	(-0.20)	(0.30)	(-0.39)	(-0.21)	(-0.06)	(0.01)	(1.13)	(0.68)	(64.67)
Log population density	-0.00278	-0.00239	-0.00313*	-0.00243	-0.00125	-0.00217	-0.00273	-0.00329	-0.00260	-0.00273***
	(-1.42)	(-1.38)	(-1.81)	(-1.42)	(-0.59)	(-1.13)	(-1.57)	(-1.25)	(-1.54)	(-6.25)
Trust	-0.0169	-0.0194	-0.0184	-0.0206	-0.0246	-0.0172	-0.0172	-0.00987	-0.00781	-0.00794
	(-1.04)	(-1.13)	(-1.14)	(-1.30)	(-1.34)	(-0.99)	(-1.07)	(-0.49)	(-0.46)	(-0.42)
Quality of government	-0.000303**	-0.000342***	-0.000309***	-0.000292**	-0.000222	-0.000310**	-0.000284**	-0.000360**	-0.000357***	-0.000180*
	(-2.49)	(-2.73)	(-2.64)	(-2.48)	(-1.49)	(-2.34)	(-2.29)	(-2.29)	(-2.79)	(-1.75)
Bike sharing	0.00235									
	(0.58)									
ICT component of the smartness definition		0.000121								
		(0.12)								
Number of Smart City projects by IBM			0.0110							
			(1.56)							
Log of average price per sqm. of average quality downtown apartment				0.00560**						
				(2.25)						
Land use: share of continuous urban fabric						-1.204				
						(-0.26)				
Urban sustainability							0.00000480			
							(1.50)			
Urban quality of life								-0.600*		
								(-1.87)		
Prior urban									-0.103	

GDP growth									(-1.32)	
Constant term	0.138*** (4.12)	0.153*** (4.65)	0.134*** (3.94)	0.116*** (3.51)	0.147*** (4.08)	0.144*** (3.91)	0.136*** (4.03)	0.439** (2.39)	0.114*** (3.33)	0.0662*** (6.70)
Estimation method	OLS	OLS	OLS	OLS	SDM	OLS	OLS	OLS	OLS	IV
λ					-0.264 (-0.47)					
ρ					3.137 (1.58)					
σ^2					0.000301*** (7.15)					
Variables instrumented	-	-	-	-	-	-				Urban smartness
Instruments	-	-	-	-	-	-				Optic fiber connectivity
Number of obs.	104	103	104	104	104	90	104	45	104	104
R^2	0.234	0.203	0.244	0.256	-	0.249	0.243	0.433	0.244	-0.019

Table 4. Identification issues

*Note: t-statistics in parentheses. *: 0.10: significance level. **: 0.05 significance level. ***: 0.01 significance level.*

Column 3 verifies instead whether results hold when we also control for the importance of private actors in driving Smart City projects. In fact, several critiques of the Smart City project revolve around the overwhelming role of private companies in fostering the narrative of the positive role of ICTs in making cities more efficient. To this aim we collected information on the cities for which one of the major players in the Smart Cities arena, viz. IBM, has Smart City projects undergoing or carried out in the past. Column 3 shows that while the parameter associated to IBM projects turns out to be statistically insignificantly associated with urban smartness, our main results hold.

Column 4 shows an additional robustness check aimed at uncovering whether urban smartness is somehow reflected in higher urban land rent, or, in other words, if smarter cities tend to be reflected in higher house prices, thus engendering a further form of income inequality.[x] Data for the average price per square meters of average quality apartments located in downtowns of the selected urban areas have been collected, and results suggest that this may marginally impact the precision of our estimates.[xi]

In Column 5 we deal instead with the possible spatial heterogeneity in our estimates. This may be due to the network dependence in the diffusion mechanism behind Smart City technologies, as well as to possible spatial externalities affecting both the independent and the dependent variables in the model (Corrado and Fingleton, 2012). In order to address these issues we also provide estimates of a Spatial Durbin specification assuming spatial dependence in both the RHS and left hand side (LHS) variables, with the use of a regular inverse distance weight matrix. Accounting for spatial heterogeneity does not change the direction of the identified correlation, but does cause a significant drop in the associated significance. Lastly, it is worth stressing that this robustness test seems not to be suggested by the standard tests for spatial autocorrelation in the residuals, that turn out to be never significant.

Column 6 tests a further hypothesis that land use affects the identified relationship. This may happen because, as discussed above, more compact cities could be structurally more efficient and thereby also find it easier to handle possible unequal effects of the adoption of smart urban technologies. This test is performed by also controlling for the share of continuous urban fabric as captured by the 2012 version of Corine Land Cover. This result does not change the direction of the identified relationship, although it does cause a decrease in the associated significance level, now barely out of the usual 10 per cent level.

Column 7 deals with yet another possible source of potential omitted bias in our estimates, linked to the recent success met by many competing definitions of what an efficiently managed city is. Among those, recently substantial attention has been drawn by the concept of sustainable cities (Haughton and Hunter, 2004; Satterthwaite, 1997). While we agree urban sustainability deserves utmost importance in the context of increasing resource limitations and with the aim to guarantee the feasibility of long-run consumption for future generations, without hampering the quality of both landscape and environment, we believe again this issue only represents an axis in our very definition of urban smartness.

Moreover, we also perform an additional robustness check by inspecting whether our results are affected by the inclusion of the measure of urban sustainability described in Section 3. Column 7 suggests that the inclusion of this additional vector does not change the main message of our results: urban smartness is still found to be negatively and significantly associated with urban income inequality. It is also worth mentioning that the additional indicator of urban smartness is found to be insignificantly associated with urban income inequality, even though marginally so (and with a positive sign).

A further consistency check for possible omitted variable bias is related to verifying whether our findings depend on the omission of the quality of life component within our empirical measurement of urban smartness. We perform this check by including a city-specific indicator of quality of life, calculated as follows. Following Lenzi and Perucca (2020), we exploit the information contained in the Eurobarometer 419 (Quality of Life in European Cities 2015), to calculate individual answers (with 40,798 European citizens interviewed) to the question "*Please tell me whether you strongly agree, somewhat agree, somewhat disagree or strongly disagree with the statement 'I am satisfied to live in [Name of the city]' "*. The percentage of people answering they strongly agree with this statement is first regressed on individual traits (including age, gender, occupation, and level of education);[xii] next, the predicted value of this regression is calculated, in order to obtain a city-specific *mean* value of life satisfaction that is net of the sorting of people who may be satisfied to live in that city for their own reasons, or individual characteristics, and not for the objective benefits the city offers in terms of quality of life. Altogether we obtain 45 observations overlapping with our database.

Results shown in Column 8 suggest that, despite the rather substantial reduction in the number of observations (down to 45 with the inclusion of the last set of controls calculated on the basis of the Flash Eurobarometer data base), the negative association between urban smartness and urban income inequality is confirmed, and, if anything, becomes larger in magnitude while also being characterized by higher significance levels. This is also reflected in a higher R^2 for this specification, which cannot be compared to other columns, though, again because of the lower number of observations. In fact, the reduction in the observations available could be not neutral w.r.t. city size: most cities in the Flash Eurobarometer used for this robustness checks tend to be on the large end of the size spectrum, and may thus lead us to identify a somewhat more coherent set of cities for this particular control.

Following the argument presented (among many) in Wheeler (2004), one may also argue that the negative relationship between urban smartness and income inequality we find could be due to the Smart Cities' average faster economic growth, since the latter is also often found to be associated with lower income inequalities. This assumption has been tested in another specification, where, along with the control variables shown in the previous specifications, in Table 4, Column 9 we also include the average urban GDP growth rate between 2008 and 2010 (the two years immediately prior to the years the main control variables in our regressions are calculated). Results for the main RHS variables remain largely unaffected, and in particular we find a negative and significant association between smartness and income inequality (which shows that this result is not driven by prior economic performance).

Finally, in Column 10 we present results of an Instrumental Variable regression that deals with possible endogeneity of Smartness w.r.t. income inequality. Our identification strategy uses a five year time lagged (2005) vector of city-specific endowment with optic fiber, which may well have represented a competitive advantage for cities in our sample to adopt Smart technologies, without however being associated to income disparities in 2017.[xiii]

Results confirm that the association between urban smartness is negative and significant at all conventional levels, while possible reverse causation can be ruled out on the basis of the IV approach. All standard tests (Underidentification, weak identification, and overidentification) are passed at all conventional levels. These last findings provide robust evidence that the main results discussed throughout this paper are robust to several robustness checks, and that the identified negative association between urban smartness and urban income inequality can be interpreted in a causal sense.

Conclusions

The academic and policy debate on the Smart City paradigm has recently produced a stream of studies arguing that the technological twist of the prevailing Smart City definitions, approaches, and policies could potentially hide severe pitfalls related to this planning approach. In the academic debate, this argument has often been revolving around the idea that the adoption of Smart technologies for managing cities would exacerbate income inequalities, by favoring layers of the income distribution that are already skilled, high-salary, and thereby capable of reaping the benefits of this paradigm.

However, to date, this proposition has never been empirically tested on a cross section of cities allowing safe statistical inference; in fact, so far the discussion mostly revolved around theories and approaches rooted more in critical reviews of the Smart City concept, rather than being based on sound empirical evidence. This paper fills this gap and proposes a set of empirical analyses suggesting that, in fact, higher levels of urban smartness are associated with lower levels of income inequality. Results hold also when controlling for several urban characteristics typically associated with income inequality: compact urban form, level of economic development, social capital, and institutional quality. Besides, and again contrary to what often argued, higher levels of urban smartness are also associated with stronger negative impacts on income inequality as we look at stronger welfare preferences against income inequalities in the lower layers of the distribution.

In order to further strengthen these results, and to rule out possible biases that may affect our estimates, we have addressed endogeneity by means of two-stages least squares. This empirical strategy confirms our main findings regarding the mitigating effect of smart characteristics on income inequality.

The answer to the research question of this paper thus seems to be a rather univocal "no": Smart Cities tend, in fact, to be more equitable from an income distribution point of view. This is rather suggestive, in that it offers a counterargument to the classical trade-off between efficiency and equity, which has also been questioned in prior works (see e.g. Martin, 2008).

As an avenue for future research, a further empirical verification to be carried out is related to looking at the impact of the adoption of Smart Urban technologies on another frequently advocated form of inequality, i.e.

the digital divide. In fact, several recent critiques against the Smart City paradigm focused on the fact that only the tech-savvy would really benefit from it.

While not yet being conclusive in this debate, our findings suggest that-once again-critiques against the adoption of smart policy approaches and measures need to be tested to avoid that radicalized and judgmental opinions prevail on hard facts and sound evidence.

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[i] For a more detailed and comprehensive systematization of the general literature on Smart Cities see e.g. Komninos and Mora (2018).

[ii] Because the choice of this geography is non-trivial, more details on the motivations for this choice are presented in the Technical Appendix.

[iii] Due to space limitations, the description and the empirical analysis in the main text refers only to the Gini index. The General Entropy Index and the Atkinson Index are discussed and analyzed in the Technical Appendix, along with the results of the corresponding regression analyses.

[iv] The European Values Study (EVS) is "*a large-scale, cross-national, repeated cross-sectional survey research programme on basic human values*", providing quantitative assessments of "*ideas, beliefs, preferences, attitudes, values and opinions of citizens all over Europe*” (EVS, 2020).

v A more detailed account of this approach, along with the results of the first stage regressions, can be found in the Technical Appendix.

[vi] We would like to thank the Handling Editor for suggesting the controls presented in Table 4, Column 7 and 8.

[vii] This information was collected for different years to maximize data availability in the sample and we have considered average values over the years. Poverty exposure data refers to the years 2016-19; environmental exposure data to the years 2009-2013; energy exposure 2010-2019.

[viii] Details on the first-stage Mincerian wage regressions and on additional robustness checks are provided for space limitations in the Technical Appendix.

[ix] As multicollinearity may potentially represent an issue in these estimates, as implicitly suggested in the works about urban scaling laws (see e.g. Bettencourt et al. 2007, and Ribeiro et al. (2020), we also verify the extent to which this affects our estimates by means of the standard Variance Inflation Factor (VIF). Results suggest that in none of our baseline model specifications multicollinearity represents an issue (as demonstrated by the largest VIF recorded in the models shown in Table 2, equal to 2.47). The largest VIF for each specification is reported in the penultimate line of Table 2.

[x] In the form of capitalized incomes, i.e. wealth.

[xi] In fact, our main results suffer from a minor loss of significance (p-value= .106).

[xii] For space limitations, results of this ancillary regression are shown in the Technical Appendix.

[xiii] The spatial distribution of optic fiber in Europe for 2005 is shown in the Technical Appendix.