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Nicolò Barbieri, Davide Consoli, Giovanni Marin & François Perruchas

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Nicolò Barbieri
Universitá di Ferrara; SEEDS (Italy)
nicolo.barbieri@unife.it

Davide Consoli
INGENIO (CSIC-UPV), Universitat Politècnica de València, Valencia (Spain)
davide.consoli@ingenio.upv.es

Giovanni Marin
Universitá degli Studi di Urbino Carlo Bo; SEEDS (Italy)
giovanni.marin@uniurb.it

François Perruchas
INGENIO (CSIC-UPV), Universitat Politècnica de València, Valencia (Spain)
franperr@ingenio.upv.es

Abstract

Climate change is a global phenomenon with markedly local manifestations. Accordingly, territories differ in terms of exposure to climate events, of capacity to adopt climate mitigation policies and of the welfare effects that these deep transformations entail. The paper brings together these threads with an empirical study of the relationship between green technology development and income inequality in US Metropolitan Areas over the period 2005-2015. We find a positive association between local patenting capacity and growing income gaps to the detriment of the least affluent. Further, higher patenting propensity in early-stage technologies has a stronger association with income inequality, whereas such a relationship dissipates at later stages of the life cycle.

JEL codes: O33; R11; D63.

Keywords: environmental technologies, technology lifecycle, inequality.

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1. Introduction

The expectation that the green transition will be just and equitable (UN, 2015) has to be aligned with the challenges associated with the reorganisation of production and of consumption activities (Marin and Vona, 2019). The consensus is that innovation is the key to tackling climate-related hazards in a timely and successfully fashion (Balta-Ozkan et al., 2015; Auci et al., 2021), and that regions and cities will play a prominent role in the roll out of candidate solutions. Within this debate are also growing concerns towards distributive issues stemming from the transition, articulated through a variety of perspectives and of methodological approaches. To illustrate, research on the social causes and consequences of climate change is replete with cross-national or cross-regional evidence that dangerous manufacturing and harmful extractive activities are overrepresented in marginal areas (Tol and Leek, 1999; Kahn et al., 2011; Berlemann and Wenzel, 2018). Likewise, studies based on the environmental justice approach identify vulnerable segments of population collectives within countries, typically identified by age and gender (Adger, 2006; Parks and Roberts, 2006). Other literature explores post-implementation outcomes, for example by assessing the effectiveness on-the-ground of policy-led initiatives for sustainable regional development (Chatterton, 2002; Haughton and Counsell, 2004; Wong, 2009).

In our view, research on the 'intended' consequences of environmental actions pays little attention to 'unintended' outcomes. Given the provision that a 'technological fix' will not suffice to tackle climate change, green technology is undoubtedly a key pillar of mitigation and adaptation strategies. The question is: could the solution to one challenge be the root of other, unforeseen, problems? That is, while there is no doubt that new green technologies are crucial to the achievement of climate policy objectives,[1] this class of innovations could trigger indirect effects that may paradoxically hamper the transition towards sustainable societies, for instance by crowding out or by leading to energy and environmental rebound effects (van den Bergh, 2013).

The present paper aims to tackle these issues by investigating the relationship between the development of green inventions and income inequality in Metropolitan Areas of the United

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[1] See Barbieri et al. (2016) for a review of this literature.

States (US) over the period 2005-2015.[2] In the framework proposed here innovation affects inequality through two main channels. The first is the distribution of returns to innovation which, according to recent literature is highly unequal within both firms and territories (Aghion et al., 2019). The second channel concerns the relationship between inequality and firms' dynamics. That is, in more competitive markets, firms' productivity is correlated with larger income shares that are translated into higher income for firms' owners, managers, developers, CEOs, inventors, etc. Therefore, stimulating the market for green inventions may favour inequality as the returns from innovative activities are unevenly distributed within (Aghion et al., 2018) and across firms (Song et al., 2019). Although these theoretical mechanisms work for conventional technologies, the aim of the present paper is to extend this framework by exploring the relationship between green technologies and inequality. The motivation of this choice is twofold. First, as reported above, triggering the development of green technologies is pivotal for the sustainable transition. As green technologies contribute to the reduction of environmental externalities (Jaffe et al., 2005), governments should create the conditions to create a market for these technologies, either by means of flexible policy tools (Pigouvian taxes or subsidies) to favour the adoption of green technologies, or by imposing their adoption via environmental standards. Exploring the side effect of such endeavour will unveil potential indirect effects on other dimensions, such as income distribution, that would call for coherent policy packages in which redistribution policies complement environmental ones. Second, green technologies are more complex, novel and exert higher impact on future technologies (Barbieri et al., 2020a). Furthermore, they tend to be at an earlier stage of maturity (Barbieri et al., 2020b, Perruchas et al., 2020). Taken together these idiosyncratic features may amplify or reduce the effects that have been observed for conventional technologies.

To explore the above, we build on Aghion et al. (2019) and test whether local green technology capacity is associated with income inequality, that is, compare whether the relationship differs from that observed with conventional technologies. Using data from the annual American Community Survey (1% sample of the US population; Ruggles et al., 2020) we build indicators of inequality at US Metro Area (MSA) level, including the Gini index and various income

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[2] A recent stream of studies explores the causes and consequences of environmental inequality (see e.g., Boyce et al., 2016; Zhang et al., 2018). In our paper we focus on income inequality given the theoretical framework of our paper that builds on the shared rewards of innovative activities.

percentile ratios. This allows us capturing different nuances of inequality, not just on the entire income distribution but also within specific portions of the upper and lower tails. To analyse MSAs' green technology capacity, we geo-localise inventor's addresses from patents (source: Patstat) in environmental technology parsed using the Y02 branch of the Cooperative Patent Classification (CPC). In so doing, we contribute to an emerging stream of studies on the geographical dimension of green technological change (see i.e., Barbieri et al., 2022; Montresor & Quatraro, 2020; Santoalha et al., 2021; Santoalha & Boschma, 2021; Castellani et al., 2022). The analysis uncovers a positive association between MSAs' environmental patenting capacity and growing income gaps to the detriment of the least affluent. The main finding is that green patenting is positively related with Gini index and, intriguingly, with percentile ratios in the lower part of the income distribution, while no significant association is found in the upper portions of the distribution. This is robust to the inclusion of various controls.

Subsequently, we articulate the analysis in terms of green technology life cycle (Barbieri et al, 2020b; Perruchas et al., 2020) to explore differential distributive outcomes along the gradient of technology development. We observe that higher patenting propensity in early-stage green technological fields has a stronger association with income inequality, and that such a relationship dissipates at later stages of the life cycle. This may explain the finding that the contribution of green patenting to inequality is much lower than that of non-green technologies. Indeed, early-stage technologies may require more time to exert their effects on productivity resulting, nowadays, in lower rewards arising from the innovative process.[3]

The paper is organised as follows. Section 2 describes the literature background of the paper. Section 3 describes our data sources and variables definition. Section 4 presents the empirical strategy and discusses the main results. Finally, Section 5 concludes.

2. Literature background

It is widely acknowledged that geography plays a pivotal role in economic growth and technological change. Clustering and shared formal and informal institutional settings favour learning, idea exchanges and, ultimately, the circulation of knowledge that is a prime engine of innovation and economic development. The uneven spatial distribution of these dynamics entails that some territories stand out more prominently, and persistently, in the innovative landscape

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[3] This issue is even more relevant in the present study since it focuses on patenting activities.

(Acs, 2003; Audretsch and Feldman, 2003; Shearmur, 2016). Some works focus on the role of consumers' income disparity on the development of a market for green products (Vona and Patriarca, 2011; Pancesa and Owen, 2014; Mantovani et al., 2017; Zecca and Nicolli, 2021). Building on the literature of demand-driven innovation, these studies suggest that pioneer (richer) consumers can afford new, more expensive products and stimulate innovative activities that reduce the price and enables poorer consumers to buy the product. However, too much income disparity prevents these mechanisms.

Our empirical analysis explores a related issue, namely spatial disparities that emerge from the capacity to generate and/or to reap the benefits of innovation development. Prior theoretical works suggest that two main channels link income inequality and innovation. The first is found in recent studies that explore the connection between patenting activity and individuals' income. Therein, wages respond to patenting through direct compensation or to labour market effects triggered by observable signals about the ability of the inventor. Toivanen and Väänänen (2012) find that the reward for inventors is around 3% of annual earnings which increases to 30% if the patent is highly cited. This is confirmed by Bell et al. (2019) who find that inventors aged between 40 to 50 with patents in the top 1% of the citations' distribution earn more than one million dollars per year. These insights are further corroborated by Akcigit et al. (2017) who exploit historical data to define the profile of inventors. The results show that inventors are better educated and are usually more skilled than non-inventors, an element that suggests how places characterised by intense inventive activities are also more unequal. Indeed, Aghion et al. (2019) observe that different measures of innovation exert a positive impact on inequality.

The second channel that connects innovation and inequality concerns firms' dynamics. As shown by Aghion et al. (2018), the benefits of innovative activities spill over inventors and are grabbed also by entrepreneurs (who obtain the largest share on the reward), white-collars and blue-collars. In addition, firms can obtain a larger income share – which translate into higher earnings for owners, managers, etc. – especially if innovative activities lead to differences in firms' productivity relative to non-innovative ones. As Song et al. (2019) indicate, the main driver of earning differentials is the rise of across-firm, rather than within-firm, inequality. This implies that the benefits stemming from innovation are not limited to workers directly involved in the process but, rather, the rewards "spill over" occupations and accrue to a larger group of workers within those firms.

While there is ample literature on the sources and the consequences of differences between territories (see reviews in Rey and Janikas, 2005; Iammarino et al, 2019), our focus is on the links between inventive activities and inequality within local areas. Explicit analysis of such relationship within regions is a relatively recent and still unexplored domain. Donegan and Lowe (2008) show that local high-tech industrial output is positively associated with inequality in US MSAs. Likewise, Lee (2011) provides evidence of positive and significant relationship between patenting and inequality in a panel of European regions. A comparative study by Lee and Rodríguez-Pose (2013) confirms the above in the context of European regions but only reports weak correlation in US cities. Such a divergence is ascribed to institutional characteristics, in particular labour market regulation and welfare systems. Breau et al. (2014) show that higher levels of patenting are a positive and robust predictor of more unequal distributions of earnings in Canadian metropolitan areas. Within-area distributional aspects are also explored in studies that use employment in high-tech industries as a proxy for local innovation. Lee and Rodriguez-Pose (2016) find no evidence of trickle-down effects on poverty in US MSAs. A study on a sample of US cities by Kemeny and Osman (2018) shows that high-technology employment has positive if modest knock-on effects on the real wages of workers in non-tradable sectors. Lee and Clarke (2019) report that growth in high-tech employment in British local labour markets is associated with lower average wages for less well-educated workers. Finally, Liu et al. (2020) provide evidence of positive association between employment in knowledge-intensive sectors and urban wage inequality in a sample of major cities in China.

Exploring whether and to what extent green innovation affects inequality is relevant by virtue of intrinsic characteristics of green technology but also of the underlying market forces. First, green innovative activities are pivotal assets to achieve long-term climate policy objectives (Popp, 2019). Second, the development of green innovation exhibits a double externality effect that reduces incentives to invest. These two market failures arise from the public good nature of both environmental capital and the knowledge content of innovation (Jaffe et al., 2005). The lack of standard markets for the provision of environmental goods and the need of government intervention to enable and boost the diffusion are likely to generate substantial extra rents (i.e. windfall profits) in favour of green technologies, with possible unintended consequences in terms of income distribution. The creation of excessive rents depends on the limited competition on the demand side, as the ultimate 'consumer' is the government, which decides over the extent

of policy support for the development and diffusion of green technologies. Third, building on the stream of studies that investigate the characteristics of green technologies (Popp and Newell, 2012; Dechezleprêtre et al., 2017), Barbieri et al. (2020a) exploit patent data to compare green and non-green inventions across different knowledge dimensions such as the complexity of the knowledge recombination process, novelty, and impact on subsequent technologies. Their findings highlight that the patent indicators employed to capture such dimensions are systematically higher for green compared to their non-green counterpart.

The present paper aims at exploring whether and to what extent the development of green technologies is related to income inequality. Recalling the theoretical mechanisms that link inequality and inventive capacity, the higher complexity and novelty of green technologies may lead to higher direct compensation for inventors involved in the patenting activity due to the rareness of skills and know-how required to develop this category of innovation, thus contributing to higher inequality with respect to non-green inventions. Moreover, high rents could also depend on governments' decisions about the degree of support in favour of the development and diffusion of green technologies, that is needed to compensate the lack of private markets for the provision of environmental goods. On the contrary, the rewards due to green invention may be lower due to the maturity of the technology – and therefore of the related market. To provide support to this connection, we further disentangle green patenting activities with respect to their level of maturity. A recent paper by Barbieri et al. (2020b) highlights that at early stages of maturity, green technologies require diversified knowledge bases that enable exploration and experimentation of competing designs. However, once a dominant design is reached and maturity characterises the technology, specialisation favours the development of green technologies. Accordingly, we expect inequality to be higher in regions that tend to invest in early-stage technologies given the novelty of the relevant know-how and the availability of skilled inventors. Nevertheless, the lower maturity of the market and, therefore, the lower rewards that can be obtained from green inventions may compensate this direct effect and reduce the extent to which green patenting affects inequality.

3. Data and variables

3.1 Data sources

We use patent data extracted from PATSTAT version 2020a as a proxy for green inventive

capacity. The database maintained by the European Patent Office contains bibliographical data on more than 100 million patent applications at the main patent offices in the world, including all the OECD countries and leading developed countries. Our unit of analysis is the INPADOC patent family, defined by the European Patent Office as "a set of patent applications that share a priority date and cover the same invention or extensions of this invention". Depending on the legal context and patent strategies, several patent applications can cover the same invention, hence increase artificially the importance of one invention.

Green patents are identified using the "Y02" class of the Cooperative Patent Classification (CPC) which refers to "Technologies or Applications for Mitigation or Adaptation against Climate Change".[4] The Y02 code is divided in 8 subclasses, related to the sector of application (e.g., "Y02E - Reduction of Greenhouse Gas [GhG] Emissions, Related to Energy Generation, Transmission or Distribution"), each one divided into groups, that we consider here as technologies (e.g., "Y02E1 - Energy generation through renewable energy sources"). We identify US patent families (green and non-green) using inventor's addresses and retrieving those who are based in the US territory, independently of the patent office to which the patent application has been filed. To further delve into the geographical dimension and obtain the Metropolitan Area of the inventors, we first identified their addresses using the geocoding service provided by the European project RISIS2 and based on the open-source geocoder Pelias. We manually checked the results and rerun the query with minor variations for those which are not found or incorrectly localised (comparing the State found in the address with the State where the geographical coordinates are projected). The second step is identifying different names of an inventor within a patent family using the Levenshtein distance algorithm and assign coordinates to all possible variations if at least one has been geo-localised. Doing so, we assigned 82.0 % of US inventors in PATSTAT 2020a, representing 3,475,292 patent families. Further, we project the coordinates on a map to associate to each patent family the MSAs it belongs to.

The use of patent data to measure innovative capacity brings about both pros and cons (Archibugi and Pianta, 1996). The main limitation concerns the presence of strategic patents that are filed by firms but without the will to further develop the invention and introduce it to the market. Moreover, not all inventions are patented since patenting requirements may not be

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[4] The CPC is a hierarchical classification that enables to identify patents assigned to specific technological fields. By exploiting the Y02 code we are able to detect patents that refer to green technologies.

satisfied by all inventions. Despite these shortcomings, patent data offer a reliable measure of inventive activities at a precise geographical level and over extended time horizons (Popp, 2005). The present study exploits the earliest priority date within the patent family, that is, the closest date to the development of the invention.

3.2 Inequality measures

Indicators of local income distribution are built on microdata from the annual American Community Survey (ACS), available at IPUMS (Integrated Public Use Microdata Series, Ruggles et al, 2020). ACS collects several socio-economic data for a 1% representative sample of the US population. Individuals are geo-localised based on their county or PUMA (Public Use Microdata Areas with 100k+ inhabitants) of residence. Based on household-level total income (before taxes and transfers), we compute indicators of personal income distribution across individuals within the same Metro Area.[5]

As a first step, we compute the Gini coefficient, a measure of the divergence between the actual income distribution and a hypothetical perfectly equal income distribution. The average aggregate (US-level) Gini coefficient for the period 2005-2017 based on our data is 0.48, growing from 0.45 of 2005 to 0.49 of 2017. There exists substantial heterogeneity in inequality across different metro areas: the bottom percentile (i.e., less unequal areas) have a Gini of 0.37 while the top percentile (i.e., more unequal areas) have a Gini of 0.57. We also compute other indicators of income inequality based on income percentile ratios and other synthetic indicators to grasp some specificities of inequality.[6] Besides being sensitivity tests, these measures allow to focus on specific measures of 'spread' of the distribution of personal income, providing additional insights of the most favoured or most harmed income levels (OECD, 2013).

3.3 Green patenting activity and the technology life cycle

Green technologies are very diverse in terms of the environmental goals that they are expected to tackle and of the stage of maturity. As such they can be hardly treated as a homogeneous body. For example, Y02 classification contains Carbon Capture, Sequestration and Storage

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[5] Following OECD (2008), we compute the average personal income for each household member as the ratio between total household income and the square root of the number of household members. This is needed to account for economies of scale in consumption for larger households.
[6] We consider the Atkinson (1970) index with inequality aversion $\epsilon=1$ and the so-called Generalized Entropy index (Shorrocks, 1980) with $\alpha=2$. Both indicators turn out to be more sensitive to inequality arising from top incomes.

technologies (Y02C2) and Energy Generation using wind (Y02E1): while the former are at early stages of development, with very few applications worldwide, the latter has been around since after World War II and are widely adopted. To account for this variety, we follow Barbieri et al. (2020b) and measure the evolution of green technologies over their life cycle. The approach exploits two dimensions: geographical ubiquity and patenting intensity. To calculate these two measures, we use all the green patent families contained in PATSTAT 2020a, previously geo-localised to assign them the inventor's country. The first dimension is the number of countries with an RTA > 1 in a certain technology per year, while the second is the number of patent families per technology per year. A green technology is in the emergence stage if patenting intensity and ubiquity are low with respect to the other green technologies, meaning that it is developed locally only by few actors. Then, technologies experience a growth phase either via an increase in patenting activity or ubiquity. Finally, a technology is mature when more countries than the average are participating to its development, but the patenting activity is low.

We compute each MSA's green patent stock per stage of the technology life cycle, and the total green patent stock. The patent stock is the stock of patent families using 15 percent depreciation rate, represented on a map of MSA on Figure 1, divided in quintiles. As expected, most green patent families are invented in the eastern half and in the south-west of the US, while there is a lower contribution from the areas located in the centre. However, the distribution of quintiles indicates an unequal distribution across MSAs: 80% of them represent 16.07% of the total patent stock, while the top 5 (areas of New York, Detroit, Los Angeles, San Francisco and San José) accounts for 23.42%. It is worth highlighting that such an unequal distribution of inventive activity over space is correlated with the distribution of income, as shown in Figure 2. Here, we see the difference between the beginning and the end of the period of 2 variables, the green patent stock and the Gini index. This positive correlation is a first hint at the possible connection between income inequality and green patenting, which we now turn to analyse more in detail.

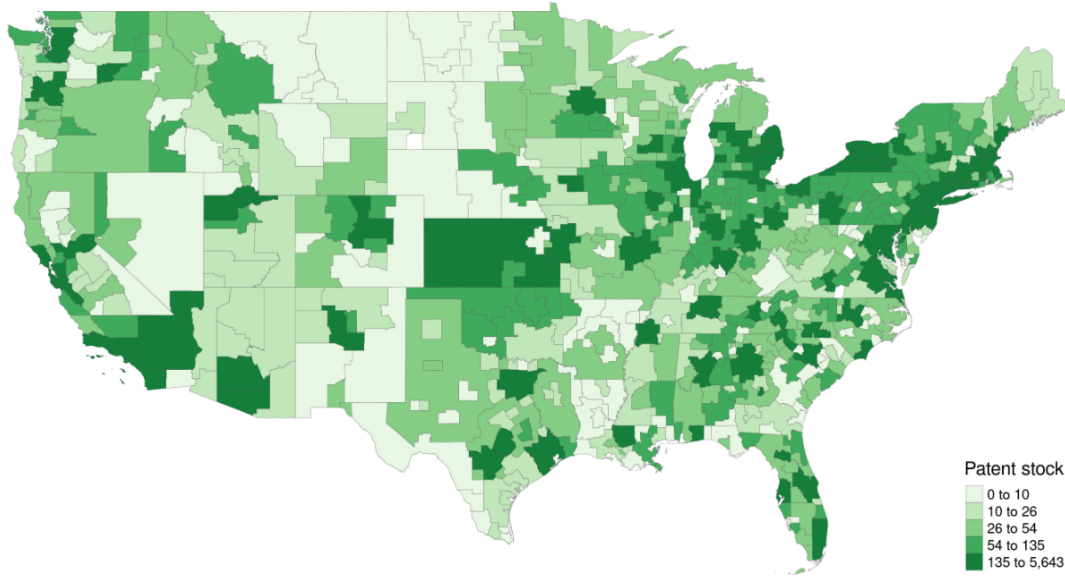Figure 1. Green patent stock per MSA in 2015

Figure 2 – Relationship between the change in Gini index (2005-2015) and the change in green patent stock (2005-2015)

4. Empirical analysis

4.1 – Model

To investigate the relationship between the development of green patents and inequality we estimate the following model on a panel of 350 MSA over the period 2005-2015:

$$Ineq_{it} = \beta \log(green\ stock_{it}) + \psi \log(nongreen\ stock_{it}) + X'_{it}\gamma + \delta_i + \rho_t + \theta_i t + \varepsilon_{it}$$

where $Ineq$ denotes the level of inequality in MSA i at time t, measured in alternative ways (i.e., Gini Index and 90/50, 90/10, 75/25, 90/25 income percentile ratios). The key explanatory variable, $green\ stock_{it}$, captures the stock of environmental-related patent families developed in the MSA. In the baseline specification, the green patenting activity is measured through the stock of patent families in all green technologies and, in a different specification, according to the life cycle stage of the technology - namely emergence, growth and maturity (Barbieri et al., 2020b). We also control for the stock of patent families in non-green technologies ($nongreen\ stock_{it}$) and for a vector of time-varying control variables at MSA level (X'_{it}).
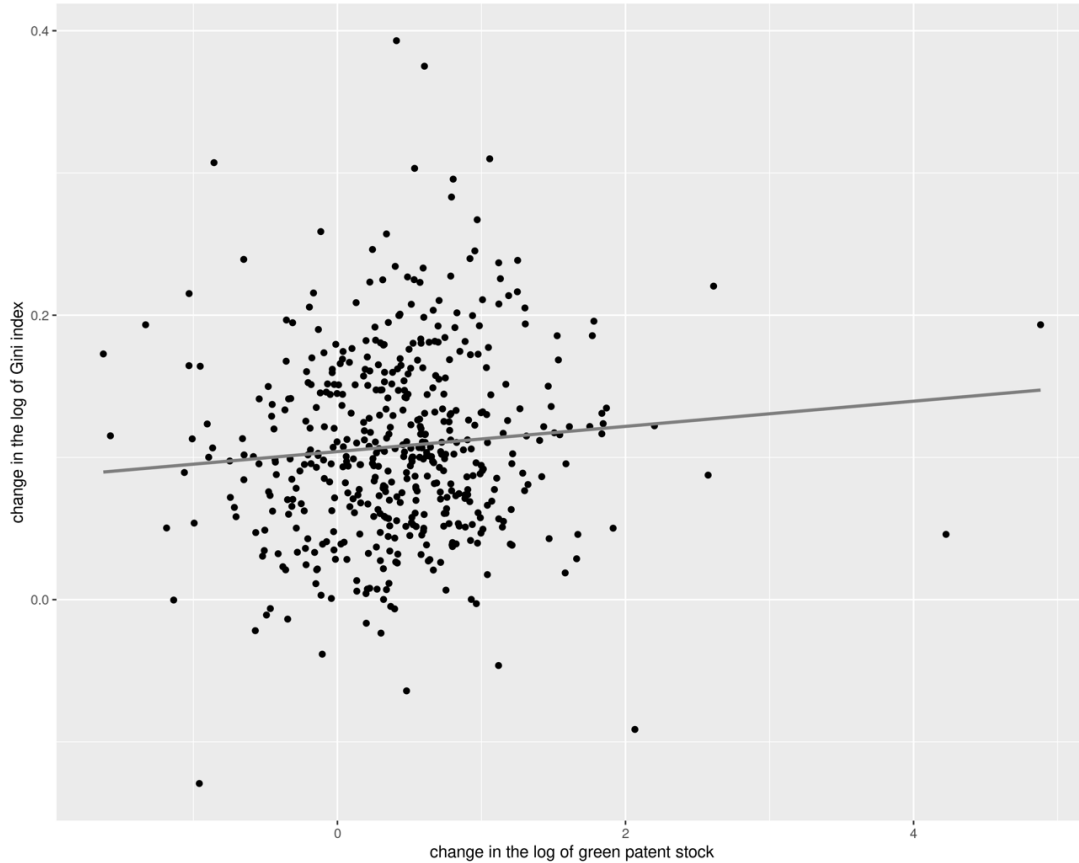
To reduce the risk of omitted variable bias, we include a series of controls. First, following Aghion et al. (2019), we control for the MSA-specific business cycle by including the unemployment rate (source: BLS-LAUS) and the location specialisation indexes of, respectively, the financial and public sectors, measured as the share of GDP associated to the financial and public sector divided by its share at the national level (data from BEA Regional Data). The set of controls includes the number of establishments with more than one hundred employees (data from County Business Patterns) as a proxy for market power and the share of employment in industries specialized in green technologies to account for the green orientation of local production systems (data from County Business Patterns).[7] In addition, usual controls employed in regional empirical studies such as average income per capita (source: BEA Regional Data) and

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[7] Following Castellani et al. (2020), we compute for each 6-digit NAICS industry the revealed technology advantage (RTA) in green technologies by considering the global stock of green and non-green patent families until the year of interest. The RTA is the ratio between green patent stock to total patent stock for the specific region and the green patent stock to total patent stock for all industries. We attribute patent families to industries by means of the CPC-NAICS concordance developed by Lybbert and Zolas (2014). Results are robust to using a dichotomous version of the RTA (dummy equal to one for RTA>1) and to using time-invariant versions of the specialisation index.

population growth (source: US Census) are included as they may influence both (green) technology capacity and inequality. To account for the possible correlation between local fiscal policies and environmental conditions, we include as a control variable the per capita revenue of state government from the exploitation of natural resources.[8] Indeed, James (2015) shows that state governments with large revenues from natural resources impose lower local taxes and increase local spending, with potentially relevant impact on inequalities. At the same time, large endowments of natural resources could be correlated with the local relative importance of environmental technologies. Moreover, to account for the bargaining power of trade unions, we measure the share of employees without union coverage (state-level data from Current Population Survey, IPUMS) and a dummy variable for states with right-to-work (RTW) laws (Ellwood and Fine, 1987).[9] Finally, δ, the MSA fixed effects, captures the idiosyncratic features that characterise each MSA and do not vary over time; ρ are time dummies that control for pre-crisis, crisis and post-crisis unobservable variation that is constant across MSAs; and $\theta_i t$ are MSA-specific linear time trends that account for unobservable heterogeneity that varies over time and across MSA. ε is the error term. Table 1 shows the summary statistics.

Table 1 – Descriptive statistics (N=3817)

Variable	Mean	SD	Min	Max
Green patent stock	81.73	224.69	0.01	2509.74
Green patent stock (Emergence)	6.33	17.18	0	203.45
Green patent stock (Growth)	29.75	91.74	0	1675.32
Green patent stock (Maturity)	62.89	183.91	0	2430.87
Non-Green patent stock	1526.03	4420.43	4.53	48490.9
Share of establishments with 100+ employees	0.02	0.01	0.01	0.05
Share of employment in green-specialised sectors	0.10	0.03	0.02	0.33
Specialisation index in finance	0.73	0.55	0	6.26
Specialisation index in the public sector	1.19	0.64	0.32	5.07
Income per capita	3.62	0.20	2.88	4.78
Population growth	0.01	0.01	-0.29	0.08
Unemployment rate	0.07	0.03	0.02	0.29
State government revenue from natural resources (per capita)	0.08	0.06	0.02	0.75
Workers w/o union coverage	0.88	0.06	0.69	1
RTW state	0.45	0.46	0	1
Workers w/o union coverage x RTW state	0.49	0.50	0	1

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[8] As this variable is measured at the state level and several MSA span over different states, we compute the weighted average for each MSA using the share of MSA population in different states as weights.
[9] Data on states with right-to-work laws are available at https://www.ncsl.org/research/labor-and-employment/right-to-work-laws-and-bills.aspx. Both for the RTW dummy and the coverage of union membership, measured at the state-level, we compute MSA-level data as described in the previous footnote.

4.2 Results

We present the results of a fixed effect model to study the relationship between green patenting and inequality in Table 2 in which: Panel A includes MSA-specific linear trends and time fixed effect, Panel B replicates Aghion et al. (2019)'s specification and Panel C includes additional control variables accounting for more specific dimensions of local labour markets and for the specificities of green technologies. The estimation indicates that non-green patenting activity is positive and statistically significant across all specifications. This is in line with the evidence of Aghion et al. (2019) about a positive correlation between total patenting and inequality.[10][11]

Similarly, our key variable of interest – stock of green patent families – is positively correlated with inequality (Table 2 – Panel A).[12] However, when we include controls to capture the characteristics of the local area, green patenting is positively correlated with the Gini index, 90/50, 75/25, and 90/25 income ratios (Panel B). Finally, by controlling for specific features of the local labour market, the green patent stock is positively correlated with the whole set of inequality measures (Panel C).[13] To provide a measure of the magnitude of such relationship, moving from a MSA at the 25th percentile of the distribution of green (non-green) patenting in 2015 to a MSA in the 75th percentile is associated with an increase in 2.1% (8.1%) in the Gini index or 2.1-8.8% (5.4-37.5%) increase in the income percentile ratios. This finding emphasises that the relationship between green innovation and inequality shows similar patterns with respect to non-green or total innovation (Aghion et al., 2019), even though the coefficients are lower than conventional types of innovation.[14]

The mechanisms underlying the relationship between both types of innovation and income inequality are, no doubt, manifold. By adding a host of control variables to our regressions, we strived to account for several sources of omitted variables that may affect the coefficients of

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[10] Aghion et al. (2019) employ top 1% income share at the US state-level. However, when they adopt the Gini index innovation variables are not significant. The difference with respect to the present study may concern the different geographical dimension or the focus on non-green patents. It is worth noting that since green patenting shows a positive and significant coefficient in Table 2 the former explanation may be the source of such difference.

[11] The controls have the expected sign. In particular, GDP per capita and the unemployment rate are positive and significant highlighting their role in explaining differences in inequality.

[12] The results are similar in terms of sign, magnitude and statistical significance of the coefficient if we do not log transform the Gini index. Results are available upon request.

[13] The result is confirmed when we adopt either the number of green patent families or the green patent families per capita as a proxies for green invention capacity. However, their coefficient is not statistically different from zero when we adopt the 90:50 percentile income ratio as dependent variable.

[14] The coefficients of green patenting stock are statistically different at 1% from the ones of the non-green patenting stock across all specifications.

interest. Instances of this case are the pervasiveness of the green economy within MSA or the institutionalisation of the labour market. However, this first finding sheds light on the theoretical mechanisms that have been disentangled above. In particular, innovation is associated with inequality via income spillover effects in occupations that are closely related to the innovation process, for example inventors, managers, et cetera. Aghion et al. (2018) offer evidence on the income spillovers of innovation within firms.

However, in order to provide an explanation for the lower coefficient of the *green stock* variable, we investigate whether the green inventive process is associated with lower rewards due to the maturity of the market for green technologies. Indeed, the opportunity to generate more economic benefits from inventive activities crucially depends on the extent to which the market rewards the output of that process. Thus, we test which type of technology is responsible for the positive effect of green patents on inequality highlighted in Table 2 by discerning between different types of green technologies based on their maturity.

Therefore, we exploit the life cycle heuristic to investigate which green technologies are associated with higher inequality. Table 3 reports the results of the model estimation grouping green patent families according to the technology life cycle stage (Barbieri et al., 2020b; Perruchas et al., 2020). We employ the stock of green patent families in green technologies that are in emergence, growing and mature stages (see Section 2.3). Overall inequality is statistically correlated to inventions in the growth phase - such as i.e., efficient water supply, technologies relating to oil refining and petrochemical industry or mitigation technologies in maritime or waterways transport. In particular, a one percent increase in the stock of green patents in those technological fields is correlated to an increase in inequality ranging from 0.008% to 0.069% depending on the indicator. To illustrate, moving from a MSA in the 25th percentile of the distribution of green patent stock in technologies in the growing phase (2015) to a MSA in the 75th percentile is associated to an 8.5% increase in the Gini index and a 42.1%, 14.6% and 17.7% increase in the 90:10, 75:25 and 90:25 income percentile ratios, respectively.

Table 2 – Baseline results

Panel A - Simple specification							
	Gini coefficient	90/50 ratio	90/10 ratio	75/25 ratio	90/25 ratio	Atkinson	Gener. entropy
log(green stock)	0.013**	0.015**	0.085**	0.038***	0.041***	0.085***	0.016
	(0.005)	(0.007)	(0.033)	(0.014)	(0.014)	(0.025)	(0.017)
log(nongreen stock)	0.191***	0.119***	0.899***	0.370***	0.399***	0.896***	0.407***
	(0.031)	(0.029)	(0.161)	(0.066)	(0.072)	(0.130)	(0.097)
Panel B - Control variables as in Aghion et al. (2019)							
	Gini coefficient	90/50 ratio	90/10 ratio	75/25 ratio	90/25 ratio	Atkinson	Gener. entropy
log(green stock)	0.013**	0.012*	0.055	0.027*	0.030**	0.062**	0.037*
	(0.006)	(0.006)	(0.034)	(0.013)	(0.014)	(0.025)	(0.021)
log(nongreen stock)	0.162***	0.104***	0.764***	0.322***	0.347***	0.744***	0.344***
	(0.028)	(0.029)	(0.148)	(0.060)	(0.068)	(0.114)	(0.083)
Specialisation index in finance	-0.002	0.003	0.007	-0.002	0.000	-0.017	-0.020
	(0.008)	(0.009)	(0.047)	(0.017)	(0.019)	(0.034)	(0.023)
Specialisation index in public sector	0.012	0.002	-0.199	-0.024	-0.043	0.047	0.044
	(0.019)	(0.017)	(0.165)	(0.041)	(0.045)	(0.069)	(0.060)
log(income per capita)	0.119***	0.027	0.533***	0.180***	0.184***	0.690***	0.303***
	(0.023)	(0.032)	(0.171)	(0.054)	(0.056)	(0.106)	(0.073)
Population growth	0.054	0.087	0.063	-0.002	-0.128	0.353	0.316
	(0.124)	(0.179)	(1.021)	(0.375)	(0.422)	(0.666)	(0.398)
Unemployment rate	0.204***	0.228**	1.866***	0.698***	0.693***	1.658***	-0.312
	(0.074)	(0.095)	(0.287)	(0.138)	(0.194)	(0.228)	(0.258)
Panel C - Full list of controls							
	Gini coefficient	90/50 ratio	90/10 ratio	75/25 ratio	90/25 ratio	Atkinson	Gener. entropy
log(green stock)	0.014**	0.014**	0.059*	0.029**	0.034**	0.064**	0.040*
	(0.006)	(0.007)	(0.033)	(0.014)	(0.014)	(0.025)	(0.021)
log(nongreen stock)	0.166***	0.112***	0.767***	0.322***	0.354***	0.723***	0.355***
	(0.030)	(0.031)	(0.151)	(0.061)	(0.070)	(0.101)	(0.089)
Share of establishments with 100+ employees	1.003	1.349	8.351	2.844	3.000	2.259	1.151
	(0.769)	(1.408)	(6.554)	(1.968)	(2.205)	(5.583)	(2.631)
Share of employment in green-specialised sectors	-0.059	-0.057	-0.306	-0.040	-0.085	-0.459	0.028
	(0.105)	(0.129)	(0.688)	(0.254)	(0.301)	(0.510)	(0.278)
Specialisation index in finance	-0.003	0.000	0.006	-0.003	-0.003	-0.019	-0.026
	(0.008)	(0.009)	(0.048)	(0.018)	(0.019)	(0.033)	(0.025)
Specialisation index in public sector	0.011	-0.001	-0.201	-0.028	-0.047	0.049	0.044
	(0.018)	(0.018)	(0.161)	(0.040)	(0.045)	(0.069)	(0.061)
log(income per capita)	0.124***	0.034	0.522***	0.174***	0.189***	0.683***	0.324***
	(0.023)	(0.032)	(0.168)	(0.054)	(0.057)	(0.110)	(0.071)
Population growth	0.036	0.070	-0.120	-0.053	-0.183	0.267	0.311
	(0.123)	(0.171)	(0.993)	(0.380)	(0.418)	(0.650)	(0.421)
Unemployment rate	0.237***	0.267**	2.195***	0.784***	0.787***	1.761***	-0.292
	(0.077)	(0.116)	(0.360)	(0.156)	(0.216)	(0.304)	(0.245)
State government revenue from natural resources (pc)	-0.053	-0.170**	0.017	-0.013	-0.138	0.468	-0.133
	(0.054)	(0.068)	(0.382)	(0.141)	(0.142)	(0.456)	(0.179)
Workers w/o union coverage	-0.105***	-0.119**	-0.022	-0.025	-0.162**	-0.094	-0.376**
	(0.039)	(0.046)	(0.197)	(0.072)	(0.079)	(0.132)	(0.163)
RTW state	-0.143***	-0.126**	-0.464*	-0.159*	-0.288***	0.603**	0.354*
	(0.049)	(0.059)	(0.275)	(0.094)	(0.099)	(0.253)	(0.208)
Workers w/o union coverage x RTW state	0.153***	0.119*	0.542*	0.149	0.293***	-0.522**	-0.328*
	(0.054)	(0.067)	(0.295)	(0.104)	(0.109)	(0.224)	(0.183)

Notes. Fixed effect model weighted by MSA population. N=3817. Standard errors clustered by MSA in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Additional control variables: MSA-specific linear trends; Great Recession dummy (2008-2009), post-recession dummy (2010-2017).

Whereas the stock of inventions in this instantiation of green technologies shows similar patterns across the different model specifications reported in Table 3, the stock of green patents in emerging technologies such as architectural or constructional elements improving the thermal performance of buildings, reducing energy consumption in communication networks or reducing

air resistance in railways, is positive and significant only when we measure inequality through the 75:25 income percentile ratio and the Generalized Entropy index. On the other hand, the coefficients of the green patent stocks in the maturity phase such as adaptation technologies in agriculture, energy efficient heating, ventilation or air conditioning or Energy generation through renewable energy sources, are not statistically different from zero across all specifications.

Table 3 – Results by technology lifecycle stage

	Gini coefficient	90/50 ratio	90/10 ratio	75/25 ratio	90/25 ratio	Atkinson	Gener. entropy
log(green stock) GT Lifecycle "emergence"	0.005	0.001	0.004	0.015**	0.015	0.015	0.021**
	(0.003)	(0.006)	(0.030)	(0.007)	(0.009)	(0.016)	(0.009)
log(green stock) GT Lifecycle "growth"	0.014***	0.008	0.069***	0.024***	0.029***	0.067***	0.033***
	(0.003)	(0.005)	(0.025)	(0.009)	(0.008)	(0.018)	(0.010)
log(green stock) GT lifecycle "maturity"	0.004	0.004	0.006	0.011	0.010	0.021	0.004
	(0.004)	(0.004)	(0.024)	(0.009)	(0.009)	(0.020)	(0.011)
log(nongreen stock)	0.164***	0.111***	0.766***	0.310***	0.344***	0.708***	0.370***
	(0.031)	(0.033)	(0.155)	(0.059)	(0.070)	(0.103)	(0.093)
Share of establishments with 100+ employees	1.091	1.340	8.739	2.496	2.779	2.753	1.546
	(0.780)	(1.443)	(6.615)	(1.991)	(2.238)	(5.827)	(2.646)
Share of employment in green-specialised sectors	-0.039	-0.050	-0.247	0.032	-0.009	-0.401	0.114
	(0.105)	(0.124)	(0.718)	(0.233)	(0.264)	(0.523)	(0.284)
Specialisation index in finance	-0.003	0.000	0.011	-0.003	-0.002	-0.015	-0.024
	(0.008)	(0.009)	(0.050)	(0.018)	(0.019)	(0.034)	(0.024)
Specialisation index in public sector	0.012	0.005	-0.202	-0.023	-0.038	0.043	0.053
	(0.020)	(0.020)	(0.166)	(0.039)	(0.044)	(0.071)	(0.063)
log(income per capita)	0.116***	0.032	0.495***	0.167***	0.180***	0.648***	0.293***
	(0.024)	(0.034)	(0.165)	(0.055)	(0.058)	(0.105)	(0.075)
Population growth	0.047	0.102	-0.007	-0.013	-0.128	0.328	0.348
	(0.122)	(0.167)	(1.016)	(0.374)	(0.402)	(0.704)	(0.424)
Unemployment rate	0.196**	0.252**	2.027***	0.692***	0.690***	1.575***	-0.400
	(0.077)	(0.125)	(0.421)	(0.161)	(0.222)	(0.311)	(0.242)
State government revenue from natural resources (pc)	-0.067	-0.176**	-0.027	-0.058	-0.177	0.412	-0.153
	(0.053)	(0.070)	(0.377)	(0.139)	(0.141)	(0.450)	(0.178)
Workers w/o union coverage	-0.104**	-0.120**	-0.021	-0.024	-0.159**	-0.096	-0.367**
	(0.039)	(0.046)	(0.196)	(0.071)	(0.078)	(0.130)	(0.166)
RTW state	-0.142***	-0.122**	-0.460	-0.151	-0.278***	0.599**	0.357*
	(0.050)	(0.059)	(0.280)	(0.093)	(0.099)	(0.255)	(0.211)
Workers w/o union coverage x RTW state	0.153***	0.116*	0.547*	0.141	0.285**	-0.514**	-0.326*
	(0.055)	(0.068)	(0.300)	(0.104)	(0.110)	(0.225)	(0.186)

*Notes. Fixed effect model weighted by MSA population. N=3817. Standard errors clustered by MSA in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Additional control variables: MSA-specific linear trends; Great Recession dummy (2008-2009), post-recession dummy (2010-2017).*

This suggests that green patenting capacity is connected to income inequality but, also, that the magnitude of this relationship is lower than that observed for conventional technologies. The life cycle heuristic enables us to advance a possible explanation of this finding: that is, since the positive relationship is mainly driven by patenting activities in early-stage green technological domains which did not yet reached a maturity stage (typically characterised by standardisation, specialisation and cost reduction activities), the rewards from the inventive process may be lower with respect to other technologies, thus leading to less income disparities.

5. Concluding remarks

The paper has brought together various threads at the intersection of economic geography and sustainability transition studies to provide novel evidence on whether and to what extent the emerging green technological paradigm impinges upon income distribution within territories.

The proviso is that innovation is the key to tackling climate-related hazards, and that regions and cities are expected to play a prominent role in the transition. At the same time, because climate change is a global phenomenon with markedly local manifestations, territories will differ significantly both in terms of exposure to climate events as well as in their capacity to adjust in the face of climate mitigation policies. These considerations reaffirm the centrality of economic geography for the study of sustainability transitions, along the lines indicated by Truffer and Coenen (2012). But, besides the issue of whether and how fast regions can adapt to the low-carbon paradigm, the current debate also emphasises distributive issues (European Commission, 2019). Geographers have long since focussed on the sources and the consequence of differences between territories (Rey and Janikas, 2005; Iammarino et al., 2019) but relatively less on inequality within local areas. The latter is especially compelling considering that societies are still at early stages of the green techno-economic paradigm, and that in various past instances the initial phase is a fertile ground for the emergence of inequalities (Bound and Griliches, 1994; Galor and Tsiddon, 1997; Vona and Consoli, 2015).

The present paper draws on and contributes these strands of literature by analysing the link between environmental technology patenting and inequality within US MSAs. This is a relevant context considering that the US are at the forefront of the nascent environmental technology frontier (Perruchas et al., 2020) and that, at the same time, there is little evidence on whether the 'green innovation rush' carries redistributive consequences within territories. Our empirical analysis is enriched by a nuanced approach whereby we differentiate developments along the life cycle to assess whether the stage of technology maturity impinges differently on local inequality. Moreover, we unpack income inequality by complementing aggregate measures, such as the Gini index, with income ratios to check whether the above association holds over different portions of the income distribution.

The main finding is that green technology patenting is positively associated with inequality. This is in line with the conclusions of Aghion et al. (2019) on a study on patenting and inequality. Our

empirical analysis corroborates their results by focusing on a particular instantiation of innovation, namely environmental-related technologies. This resonates with the expectation that weak conditions for the emergence of 'standard' markets for the provision of environmental goods entail government intervention which, in turn, generate substantial extra rents and unintended distributional consequences. The correlation with income distribution we observe, however, is lower in magnitude compared to conventional, non-green technologies. Moreover, the correlation between green patenting and inequality is contingent on the stage of maturity of the green technology. In particular, inequality is higher in MSAs that lead the way in the development of new technologies, therefore at early stages of the life-cycle. These preliminary results shed some light on the spatial contingencies that affect inequality. Therein, it seems that green innovation does not differ from conventional forms of innovation except in the magnitude of this correlation.

These findings suggest that, in line with the literature on the indirect effect of eco-innovation, also the development of green technologies may generate higher income disparities. This argument, however, does not minimise the role of green technologies. Instead, it reinforces the idea that to fully exploit the benefits generated by the green technologies, it is necessary to acknowledge the systemic nature of the sustainable transition, which calls for coherent policy packages that embrace different perspectives such as income redistribution.

Besides contributing to the literature mentioned above, the present paper speaks to the emerging debate on the need for a more balanced assessment of the benefits and the costs of innovation. This is relevant for scholars of economic geography and innovation alike, other than to policy makers. The common thread across empirical studies is that the logic of local economic development based on the promotion of high-innovative activities need critical rethinking (Bartik, 1993; Goetz et al., 2011). If the ultimate goal of economic development is to create economic prosperity – of which environmental quality is a key ingredient – innovation, entrepreneurship and private sector investments are but means to that end (Haider, 1986; Feldman et al., 2016). Under this perspective, inequality may well be a physiological component of the ratio between equity and efficiency, and that these two should not been seen as substitutes but, rather, as complements (Stiglitz, 2012). Beyond the remit of economic geography, there is growing discomfort with the acritical stance that the policy agenda based on the pillars of competition, productivity and wealth creation through technology turns a blind eye on significant

negative social outcomes ranging from the erosion of human rights (Giuliani, 2018) to environmental disasters (Lohmann et al., 2007; Griggs et al., 2013; Biggi and Giuliani, 2020). In this spirit, the present paper provides evidence of redistributive dynamics associated to innovation in environmental technologies, with a view to promote awareness of one of the 'dark' sides of the widely celebrated green transition.

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