Economic Complexity and the Environment: Evidence from Brazil

Julia Swart and Lisa Brinkmann

Abstract Brazil is a heterogenous country with respect to, among others, economic complexity, economic development and environmental quality. This paper examines the relationship between economic complexity and key environmental variables in Brazil. We deviate from the Environmental Kuznets Curve (EKC) literature by focusing on economic complexity instead of economic development alone to explain cross-section and time-series variation in a range of environmental variables. Our motivation for considering economic complexity as a main explanatory variable lies on the consideration that low economic complexity is associated to products which are peripheral on the product space. These are products which are less connected to other products, limiting the opportunities for other economic activities, and therefore limiting the impact on the environment. As economic complexity increases more opportunities are created, the product space becomes denser, and pollution increases. However, at a high enough level of economic complexity, the structural changes bring knowledge-intensive industries, which demands higher-skilled labour force and wider skills of occupations. At this point, economic complexity is associated to decreasing environmental degradation. Using panel data for Brazil we find that waste generation decreases, but forest fires increase with rising complexity. Complexity is not associated to more deforestation or air pollution.

Keywords Economic complexity · Brazil · Environmental degradation · Solid waste generation · Deforestation · Forest fires · Air pollution

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1 Introduction

In September 2015 the Heads of State and Government met at the United Nations Headquarters in New York, when they agreed on 17 Sustainable Development Goals (United Nations 2015). These goals linked sustainable development to three perspectives: economic, social and environmental; and emphasized the challenge to alleviate poverty and environmental degradation. Brazil is an upper-middle-income economy, with a GDP per capita of around 11,000 dollars in 2016 (World Bank WDI). It ranked 44 out of 85 countries in terms of Economic Complexity in the same year (Observatory of Economic Complexity). Brazil is also a country of inequalities, where close to 13% of the population was unemployment in 2017 (World Bank, WDI) and poverty reached 8% of the population in 2015 (World Bank, WDI).[1] Embracing the Sustainable Development Goals is vital for Brazil, given these economic and social challenges, but also given the pressure that economic development places on the environment. In 2016 around 40 percent of the Brazilian population lived in urban agglomerations of more than 1 million people (World Bank, WDI). As in many developing countries, people agglomerate in big cities in search for better opportunities. This agglomeration can create a coordination challenge at the cost of inadequate provisions of services and infrastructure, which contributes to environmental problems (such as air pollution, and open-air waste disposal).

At the same time United Nations (2015) argues that we live in a “time of immense opportunity”. A time in which “the spread of information and communications technology and global interconnectedness has great potential to accelerate human progress, to bridge the digital divide and to develop knowledge societies, as does scientific and technological innovation across areas as diverse as medicine and energy” (p. 5). In this sense, economic agglomeration, when tied to technological advances and access to knowledge can stimulate the adoption of cleaner production methods and infrastructure.

The empirical literature analysing economic factors driving environmental degradation set a central role on economic growth (Stern 2017). Nonetheless, Stern (2017) argues that for truly understanding what reduces pollution, we need to understand “the nature of the factors that are not related to economic growth” (p. 8). The Environmental Kuznets Curve (EKC) hypothesis suggests an inverted U-shaped relationship between various indicators of environmental degradation and income. Accordingly, environmental degradation increases during the early stages of economic development, until a turning point level of income is reached. From this point, with rising incomes, economic development ultimately leads to enhanced environmental quality. The EKC is, however, silent with respect to how income level affects environmental quality. Economic development could be capturing institutional quality, preferences, education, economic structures (e.g. sectoral composition), among others. An empirical analysis, should thus try to include these direct determinants of environmental quality. Leaving them out could wrongly indicate that economic growth is all it needs

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[1] Poverty headcount ratio at \$3.20 a day (2011 PP) (% of population).

to improve environmental indicators (see also IBRD 1992; Arrow et al. 1995; Stern 2002 and Dasgupta et al. 2002).

Concomitantly with the debate in the policy sphere, the empirical evidence has been far from unambiguous. Numerous researchers have tested the EKC hypothesis for a variety of countries, environmental degradation indicators and econometric techniques. Some studies find evidence for an inverted U-shaped relationship between urban pollution—for instance due to sulphur dioxide and suspended particles—and income (e.g. Grossman and Krueger 1991; Shafik and Bandyopadhyay 1992; Panayotou 1993; Selden and Song 1994). Other studies, however, find these local pollutants to be positively correlated with income (e.g. Stern and Common 2001; Stern 2002; Perman and Stern 2003; Liu et al. 2017). A positive relationship with economic development is also found for carbon dioxide emissions, deforestation, and alternative indicators of environmental degradation (e.g. Shafik and Bandyopadhyay 1992; Holtz-Eakin and Selden 1995).

This paper adds to the EKC literature by considering a new possible driving force of environmental quality: economic complexity. The underlying motivation for analysing the relationship between economic complexity and the environment is the consideration proposed by Hausmann et al. (2014) that economic development is driven by knowledge. Hausmann et al. (2014) show that economic complexity is a highly accurate predictor of growth. According to the authors, economic complexity reflects the amount of knowledge that is embedded in societies, consequently mirroring the productive structure of an economy. Differences in economic complexity account for the diversity and sophistication of the products exported by each country. In complex economies, individuals build large networks that enable them to combine knowledge more easily and ultimately produce an extensive variety of knowledge-intensive goods.

Contrary to the traditional EKC hypothesis, which relies on the notion that environmental quality is a luxury good, the rationale for exploring the relationship between economic complexity and the environment relates closely to the technical capabilities of a country's industry. We hypothesize that, after a threshold level of economic complexity has been reached, increasing economic complexity is accompanied by knowledge embedded in technology and human capital which is necessary to limit environmental degradation. Simple economies usually focus on the production of raw minerals or elementary agricultural goods and, accordingly, cause only limited environmental degradation. With the take-off of industrialisation and the diversification of production, economies become gradually more complex. At the same time, however, environmental degradation soars. Finally, at higher levels of economic complexity, structural changes towards knowledge-intensive industries takes place. This rise in economic complexity provides the knowledge and, hence, the technology needed for economies to become "green". Examples are the production of energy-efficient goods and electric cars; the generation of energy with renewable resources such as photovoltaics, wind, or biomass; or innovations such as recycling, energy grid integration, and cradle-to-cradle design. A high level of productive knowledge is necessary for technological breakthroughs like these to get under way. When economies eventually reach such a level of complexity, environmental degradation will level off and start to decline.

This paper investigates the validity of the complexity-environment nexus for the case of Brazil. More precisely, we analyse the extent to which the productive structure in different Brazilian municipalities, states and metropolitan regions influences the quality of the environment. Brazil's recent economic history, marked by the transition from a closed to an open economy in less than three decades; the importance of the environment for the industry and society; and regional diversity provide a strong case to conduct a study specifically for Brazil.

Until the 1980s and early 1990s, Brazil's economy was characterised by strong import substitution policies, macroeconomic policies aimed at stabilising the prevalent hyperinflation, and an industry producing almost exclusively for the domestic market. With the creation of the free trade area Mercosur in 1991, subsequent privatisations, and the withdrawal of the state from production, Brazil experienced a period of relatively high growth rates (Lo and Hiscock 2014). Figure 1 shows that Brazil experienced positive growth throughout the mid-1990s and early 2000s. Higher competitiveness and an ensuing export boom—especially of agricultural products such as soybean and cocoa—helped the country position itself as a promising emerging market. During the same period, however, Brazil's economy became steadily less complex, a fact that can certainly be attributed to the relevance of agriculture as a driver of its economic development. Ranking as the world's 29th in terms of economic

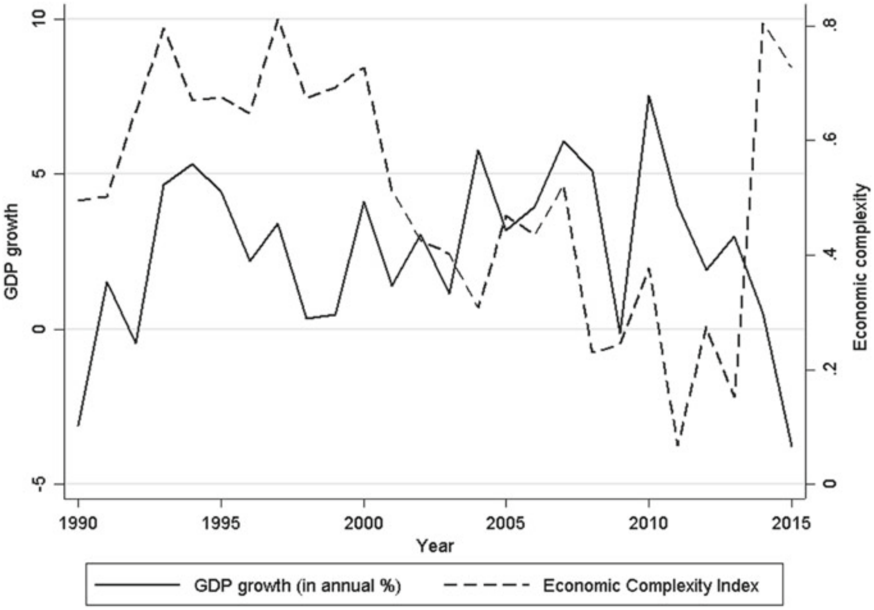

Fig. 1 Economic growth and economic complexity in Brazil (1990–2015). *Data sources* World Bank, Observatory of Economic Complexity

complexity in 1995, the country ranked 54th in 2014 (Observatory of Economic Complexity 2017). Interestingly, while Brazil's current economic and political crisis has stopped this positive growth trend altogether, the country has seen its position in the global economic complexity ranking strengthen simultaneously.

Alongside the prosperity brought about by Brazil opening up to international trade, severe environmental problems emanated during this period. The country's most notorious environmental problem is the deforestation of its rain forests. Deforestation in Brazil has been mainly driven by the expansion of agriculture. Hundred hectares of the Amazon forest have been cut or burnt down each year for the large-scale settlement of farmlands designated for cocoa, coffee, soybeans, sugarcane and cattle pastures. By no means exclusive to the Amazon basin, these practices have also reached other regions in Brazil (e.g. the tropical savanna of the Cerrado).

Moreover, urbanisation rates have risen dramatically in the last two decades. According to the World Bank (2017), approximately 85% of the more than 200 million inhabitants in Brazil lived in urban areas in 2015. Particularly in the economic hubs of São Paulo, Brazil's largest city and one of the largest urban areas worldwide, Rio de Janeiro and Belo Horizonte, air pollution as well as waste generation represent serious environmental problems.

The paper is structured as follows. Section 2 briefly reviews the EKC literature, first summarising the findings on the world or specific subsets of countries, and secondly summarising Brazil-specific findings. Section 3 describes the proposed model, the data used and the methodology chosen. Section 4 presents the empirical results for four environmental degradation indicators analysed: Section 4.1 for solid waste generation, Sect. 4.2 for deforestation, Sect. 4.3 for forest fires, and Sect. 4.4 for air pollution. Section 5 concludes by outlining the implications of our results and the possible scope for improvement and extension.

2 Literature Review

The EKC has its roots on the seminal work by Grossman and Krueger (1991), the first authors to explicitly find evidence for an inverted U-shaped relationship between indicators of environmental degradation and income. Following their work other empirical papers found evidence for an EKC (see e.g. Shafik and Bandyopadhyay 1992; Panayotou 1993; and Selden and Song 1994). Notwithstanding the empirical evidence of the first EKC studies, Stern et al. (1996) examine the concept of the EKC critically on both theoretical and empirical grounds. In a later review, Stern (2004) argues that most of the EKC literature of the 1990s is empirically weak, as it fails to take into account statistical properties likely to influence the estimation results (such as heteroskedasticity, serial correlation and cointegration), and the possible existence of simultaneity and omitted variables bias. Furthermore, the coefficients estimated in the first EKC studies differ substantially depending on the subsample used. Stern (2004) notes that no or only weak evidence for the EKC hypothesis can be found when accounting for diagnostic statistics, using appropriate techniques, and performing specification tests. In addition, studies using more representative data find sulphur dioxide emissions and concentrations—traditionally a showcase for the EKC hypothesis—to be positively correlated with income, a finding that is in line with the estimation results for other environmental degradation indicators.

Stern and Common (2001) reduce misspecification problems by using first-differenced data when estimating the EKC. The authors find that the relationship between sulphur dioxide emissions and income is positive in both high- and low-income countries. Stern (2002) applies an emission-decomposition model and finds that sulphur emissions rise with increasing income at all levels of income. Many other test the EKC hypothesis and find mixed results (e.g. Suri and Chapman 1998; Perman and Stern 2003; Tao et al. 2008; Managi and Jena 2008; Mills and Waite 2009; Jalil and Mahmud 2009; Iwata et al. 2010; Fodha and Zaghdoud 2010; Fosten et al. 2012; Saboori and Sulaiman 2013; Al-Mulali et al. 2015).

The empirical evidence is not more compelling in Brazil-specific studies. The empirical literature investigating the possible existence of an EKC for Brazil focus on the link between deforestation and economic development in Brazil. Santos et al. (2008), for instance, analyse 782 municipalities of the Amazon basin from 2000 to 2005, and find support for the EKC hypothesis. Oliveira et al. (2011) analyse these same municipalities for 2001–2006, but do not find evidence for a deforestation EKC. The authors include a rich set of additional explanatory variables, such as cattle, agricultural activity, vegetable extraction, forestry, population density, rural credit, annual dummies, and deforestation rate in the previous year. Gomes and Braga (2008) also analyse deforestation rates in the Amazon region and find fairly mixed evidence for the EKC. Depending on the functional form applied, the authors find either an inverted U-shaped or an N-shaped relationship between the deforestation rate and income.

Teixeira et al. (2012) investigate the existence of a deforestation EKC in 139 municipalities of the state of Mato Grosso in 2006, one of nine states constituting the Amazon River basin region. The authors control for spatial effects and add a rich set of additional explanatory variables, including per capita wood extraction and a ratio of cattle units over area destined for cattle. The findings depend strongly on the functional form chosen, thus suggesting a weak relationship between deforestation and income. Also controlling for spatial effects, Colusso et al. (2015) analyse data for the year 2008 related to 1306 municipalities constituting the Cerrado biome. The empirical evidence of this study is similarly mixed, ranging from an inverted U-shaped to a U-shaped or N-shaped relationship.

To the best of our knowledge, besides the abovementioned papers focusing on deforestation there is only one paper which examines alternative indicators of environmental degradation to test for an EKC for Brazil. Sousa et al. (2008) proxy environmental degradation by defining the deficit in drinking water, in basic sanitation, and in waste collection as dependent variables. Using a dataset containing 5507 municipalities in the years 1991 and 2000, the empirical evidence suggests that the relationship between each one of these three indicators and income per capita is U-shaped.

3 Model, Data and Methodology

3.1 Model and Data Description

The aim of this paper is to examine the extent to which the economic complexity of municipalities, states and metropolitan regions in Brazil affects the quality of their environment. We hypothesize that initially environmental degradation rises with economic complexity, but subsequently falls as structural change towards knowledge-intensive industries takes place, allowing for environmental-friendly technologies and products. We expect the relationship between environmental degradation—in terms of pollution or the extraction of natural resources such as forest resources—and economic complexity to be quadratic. In order to test this hypothesis, we estimate the following baseline specification:

$$ENV_{it} = \alpha_i + \beta_1 ECI_{it} + \beta_2 (ECI_{it})^2 + \varepsilon_{it} \qquad (1)$$

Our dependent variable, *ENV*, denotes four indicators of environmental degradation in Brazil, available at various disaggregation levels. We selected the regional level of the data based on its availability. Data on domestic solid waste generation is available for the municipalities in the state of São Paulo, the most economic complex Brazilian state. Deforestation rates are available for municipalities in nine states constituting the Amazon basin region. Data on forest fires is available at the state-level. Lastly, air pollution data is available for Brazilian metropolitan regions.

We employ panel regression techniques to estimate Eq. (1). Accordingly, $i = 1, \ldots, N$ indexes each municipality, state or metropolitan region, and $t = 1, \ldots, T$ refers to the time periods covered in the different panels. Parameter α_{i} allows for the possibility of time-invariant effects specific to the respective municipalities, states or metropolitan regions, and ε_{it} is the stochastic error term.

Solid Waste Generation

First, we analyse the relationship between solid domestic waste generation and economic complexity in the municipalities constituting the Brazilian state of São Paulo. Yearly, the Companhia Ambiental do Estado de São Paulo (CETESB), the state's agency for the control and monitoring of polluting activities, publishes estimates on the average solid waste generated domestically in each municipality in total tons per day. For our analysis, we converted these estimates into solid waste generated per capita in kilograms per day. Our panel contains data on up to 455 municipalities and covers the period from 2003 to 2011.

Deforestation

The second environmental degradation indicator we examine is the deforestation of the Amazon rainforest, based on the PRODES database. PRODES is a project by the Instituto Nacional de Pesquisas Espaciais (INPE), Brazil's National Institute for Space Research, which monitors the deforestation of the Amazon via satellite. PRODES has been publishing the annual deforestation rates (in square kilometers) of the municipalities constituting the Amazônia Legal region since 1988, and has played an important role as guidance for the Brazilian government in terms of environmental policies. Our panel comprises 760 municipalities in the nine states constituting the Amazon basin region and ranges from 2002 to 2014.

Forest Fires

We further examine the relationship between forest fires and economic complexity. Yearly, vast forest areas are burnt in Brazil to obtain free space for agricultural production and pasture (cf. Watts 2012; Mazzetti 2016). The Instituto Brasileiro de Geografia e Estatística (hereafter IBGE), Brazil's Institute of Geography and Statistics, provides data on the annual number of forest fires (measured in number of heat sources) for the 26 Brazilian states and the federal district between 2002 and 2009.

Air Pollution

Lastly, the IBGE provides data on various air pollutants for the Brazilian metropolitan regions of Belo Horizonte, Curitiba, Grande Vitória, Porto Alegre, Recife, Rio de Janeiro, Salvador and São Paulo. The air pollution indicators, measured in micrograms per cubic meter, include the annually observed maximum and average concentrations of sulphur dioxide, nitrogen dioxide, total suspended particles (TSP), and ultrafine particles (PM10). Data on maximum concentrations of carbon monoxide and ozone is also available. Our panel covers the years 2002–2009.

Economic Complexity Indicator

Our main independent variable, ECI, denotes the Economic Complexity Index (hereafter ECI), an innovative index developed by Hausmann and Hidalgo (Hausmann et al. 2014). The ECI captures the productive capacity of an economy by taking into account the complexity of its products,[2] considering their diversity (i.e. the number of products the economy exports) and ubiquity (i.e. the number of economies that export a given product). Ultimately, this index quantifies the complexity of an economy in one single number, with more complex products being exported by a smaller number of economies, as they require more sophisticated productive knowledge to be produced (Hidalgo and Hausmann 2009; Hausmann et al. 2014). Following the EKC concept, we also include the square term of the ECI, $(ECI)^2$.

The visualisation tool DataViva expanded the index for the specific case of Brazil. Using information compiled by the Brazilian Secretariat of Foreign Trade (SECEX) and the Ministry of Development, Industry and Foreign Trade (MDIC), DataViva has gathered high-quality historical data on Brazilian international trade flows to

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[2] More precisely, the ECI is calculated as the average complexity of products exported by a specific economy with international comparative advantage, weighted with the share of exports by the said economy.

construct the ECI for Brazilian municipalities and states. As the index is not available for Brazilian metropolitan regions, we constructed it as the average over the ECI of Brazilian municipalities constituting the respective metropolitan regions.

Control Variables

We include income, its square, and a set of control variables to our baseline specification:

$$ENV_{it} = \alpha_i + \beta_1 ECI_{it} + \beta_2 (ECI_{it})^2 + \beta_3 \frac{GDP_{it}}{P_{it}} + \beta_4 \left(\frac{GDP_{it}}{P_{it}} \right)^2 + X'\gamma + \varepsilon_{it} \quad (2)$$

As a measure of economic development, we include GDP per capita (*GDP*/*P*) in the different municipalities, states and metropolitan regions analysed. The Instituto de Pesquisa Econômica Aplicada (hereafter IPEA), Brazil's Institute of Applied Economic Research, provides data on GDP per capita for the Brazilian states. We use data from IPEA to construct this variable for municipalities and metropolitan regions. GDP per capita is denoted in thousand constant 2010 Brazilian Reais for states, and in thousand constant 2000 Brazilian Reais for municipalities and metropolitan regions.

X denotes a set of control variables that may affect the different environmental degradation indicators. As far as data is available, we include one or more measures of population density, urbanisation, education and trade openness. For the analysis on deforestation rates and forest fires, we also include a set of agricultural variables.

Following the example of Gomes and Braga (2008), Oliveira et al. (2011), Teixeira et al. (2012), Colusso et al. (2015), among many others, we include population density (in number of inhabitants per square kilometer) as an explanatory variable. Available at all disaggregation levels, we constructed this variable using IPEA data. To measure urbanisation, we include the ratio of total urban to total rural population, constructed with IBGE data. This variable is available for Brazilian states and metropolitan regions. We expect both variables to have a detrimental effect on the environment, as more densely populated and urban areas are likely to exert more pressure on the environment, having hence a positive sign.

As Managi and Jena (2008) point out, a rise in overall educational levels, but specifically in higher education, is usually accompanied by increased environmental awareness, ameliorating eventually the quality of the environment. We therefore control for education, expecting the correlation with environmental degradation to be negative. We include the average years of education for people aged 25 or older. Alternatively, we follow Castilho et al. (2012) and include the share of the economically active population (aged ten or higher) with upper-intermediate to higher education, which comprises individuals with more than eleven years of education. The first educational variable comes from IPEA and is available at the state-level, whereas the second one was constructed with IBGE data and is available for states and metropolitan regions.

Analogously to Iwata et al. (2010), Jalil and Feridun (2011), Nasir and Rehman (2011), Al-Mulali et al. (2015), we include a trade openness ratio as independent variable. Using UN Comtrade and IPEA data, we constructed this ratio as the sum of exports and imports over GDP. The ratio is denoted in constant 2010 Brazilian Reais at the state-level, and in constant 2000 Brazilian Reais at the metropolitan region- and municipality-level. According to Antweiler et al. (2001) as well as Cole and Elliott (2003), the effect of trade on the environment can be decomposed into three effects: scale, technique, and composition effect. The scale effect relates to the increase in overall economic activity ensuing from intensified trade, being hence detrimental to the environment. In contrast, the technique effect improves the quality of the environment due to more environmentally-friendly production brought about by international trade. Production changes either because of increased (domestic) competition, forcing the least energy-efficient firms to leave the industry, or the import of cleaner technologies. The composition effect can be positive or negative and refers to the changes in the industrial structure of an economy arising from international trade. A country or region will specialise on the production of goods for which it has a comparative advantage, which can be in cleaner or more polluting industries. Overall, the net effect of trade openness on the environment is theoretically ambiguous.

As Selden and Song (1994), Grossman and Krueger (1995), Antweiler et al. (2001), and Fosten et al. (2012), among others, we include a time trend to capture technological advances and changes in environmental awareness that are not related to either income or economic complexity.

Finally, we include an additional set of agricultural variables withdrawn from IPEA for our analyses of deforestation rates and forest fires in Brazilian municipalities and states. Various authors (e.g. Margulis 2003; Brown et al. 2005; Aguiar et al. 2007; Miragaya 2008; Vera-Diaz et al. 2008) investigate the drivers of deforestation in the Amazon rainforest, identifying agriculture—most notably in terms of cocoa, coffee, sugarcane and soy production—and cattle as the main culprits.[3] We follow Colusso et al. (2015) and include total harvested and total planted area, both in hectares, as explanatory variables.[4] We expect the agricultural variables to be positively correlated with deforestation and forest fires. In other words, we expect larger areas in the Amazon rainforest to be destroyed, and more forest fires to be observed, when there is an expansion of agricultural activity in the municipalities of the Amazon basin region and in Brazilian states.

Table 8 in the Appendix provides a detailed list of all the variables used in our analysis (in regressions or, whenever necessary, for the construction of variables) and their sources. Tables 9, 10, 11 and 12 contain descriptive statistics for the variables in the four panels.

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[3] Aguiar et al. (2007) state that 70% of the total deforested area in the Amazon Basin is destined for cattle production. 13 and three per cent were transformed into temporary and permanent harvests, respectively.

[4] Oliveira et al. (2011) and Teixeira et al. (2012) add harvested area for the aforementioned agricultural products (in hectares) and cattle units per square kilometre as control variables. IPEA provides data on harvested area by agricultural products, but the panels are rather incomplete and lead to a drop in the number of observations when employed.

3.2 Methodology

Our choice of estimation approach is driven by two main considerations: whether the correlation between time-invariant region-specific effects and all of the explanatory variables is zero; and whether the error term is idiosyncratic. We assume strict exogeneity, that is, all the explanatory variables to be uncorrelated with the error term.

Intuitively, the assumption of zero correlation between time-invariant region-specific effects and all the explanatory variables is unlikely to hold, as industrial policies within the different Brazilian municipalities, states and metropolitan regions are likely to be correlated with characteristics and features of these subregions. Omitting them could thus be an important source of bias. Unlike in the random effects approach, which assumes that these time-constant specific effects are randomly distributed across the subregions, fixed effects and first differences estimation allows for this correlation to be nonzero.

We compute first differences estimates and conduct a Breusch-Godfrey test for autocorrelation in order to choose between the first differences and fixed effects approach. For our analysis on deforestation, forest fires, maximal sulphur dioxide concentrations, and average ultrafine particle concentrations, first differences estimates are preferred over fixed effects estimates. The Breusch-Godfrey results indicate that the differenced error term is idiosyncratic. In other words, fixed effects estimation is non-stationary with these datasets. Consequently, results could be biased, as the error terms have a unit root and are highly persistent in the time-series dimension. For solid waste generation, and the other air pollution indicators, the error term is idiosyncratic, allowing for the use of fixed effects. Constant region characteristics are differenced out or time-demeaned, respectively.

To correct for heteroskedasticity and autocorrelation, which are data properties found in virtually all indicators after conducting Breusch-Pagan and Breusch-Godfrey tests, we use clustered standard errors at the municipal, state, and metropolitan region level.

4 Empirics

4.1 Solid Waste Generation

Table 1 reports the fixed effects estimates for our analysis on the relationship between solid waste generation and economic complexity in Brazilian municipalities in the state of São Paulo from 2003 to 2011. In our baseline regression, we follow Eq. (1) in Sect. 3.1 and regress per capita solid waste generation on the ECI and its square term. Since the two coefficients are not statistically different from zero, we exclude

Table 1 Domestic per capita solid waste generation (fixed effects estimation)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: solid waste generation p.c.						
ECI	−0.00337	−0.00363***	−0.00363***	−0.00363***	−0.00361***	−0.00360***	−0.00520*
	(0.00256)	(0.00137)	(0.00136)	(0.00138)	(0.00133)	(0.00134)	(0.00282)
(ECI)^2	−0.000147						0.000152
	(0.000109)						(0.000140)
GDP p.c.		0.00185***	0.00184***	0.00171***	0.00137***	0.00114**	0.00117**
		(0.000513)	(0.000506)	(0.000561)	(0.000415)	(0.000485)	(0.000482)
(GDP p.c.)^2		−1.5e−05***	−1.49e−05***	−1.39e−05**	−1.12e−05***	−9.67e−06**	−9.81e−06**
		(5.68e−06)	(5.60e−06)	(5.91e−06)	(4.09e−06)	(4.44e−06)	(4.41e−06)
Population density			5.10e−06			−2.04e−06	−2.08e−06
			(1.00e−05)			(1.10e−05)	(1.12e−05)
Trade openness				−0.000647*		−0.00151*	−0.00150*
				(0.000359)		(0.000864)	(0.000860)
Year					0.00105	0.00118	0.00118
					(0.000663)	(0.000929)	(0.000930)
Constant	0.389***	0.373***	0.370***	0.391***	−1.736	−1.964	−1.979
	(0.000696)	(0.00407)	(0.00727)	(0.00467)	(1.330)	(1.859)	(1.861)

(continued)

Table 1 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: solid waste generation p.c.						
Observations	3169	2812	2812	2253	2812	2253	2253
# of municipalities	455	448	448	360	448	360	360
R-squared	0.002	0.002	0.002	0.002	0.003	0.003	0.003
Adjusted R-squared	0.00116	0.00108	0.000747	0.000100	0.00202	0.000386	6.84e−05

Notes Standard errors, in parentheses, are clustered at the municipality-level. *Interpretation* ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

the square term in the subsequent specifications to allow for a linear relationship between the environmental degradation indicator and complexity.

Column (2) reports the estimation results of Eq. (2), which includes GDP per capita and its square term as additional explanatory variables. The ECI estimate is now statistically significant and negative, indicating that a rise in economic complexity leads to a reduction of the amount of solid waste generated daily per person. For concreteness, individuals generate an average of 3.63 g less waste per day if the complexity index increases by one unit. This finding shows that waste generation has a negative relation with economic complexity, which suggests that individuals generate less waste in more complex municipalities. An intuitive reasoning is that in more economic complex municipalities, there is a higher percentage of tertiary sectors which generate less waste than manufacturing sectors. Another reason could be that more complex economies have more knowledge about how to make more efficient use of resources and materials, leading to less waste.

Both GDP per capita and its square term are significantly different from zero. With the square term bearing a negative sign, the relationship between solid waste generation and income per capita is inverted U-shaped. This finding supports the existence of a waste generation EKC for the state of São Paulo.

The two significant relationships found in specification (2) are robust to the inclusion of individual controls and the complete set of variables. Population density and the time trend are unrelated to solid waste generation. In contrast, trade openness has a significant and negative impact on the dependent variable, suggesting that individuals generate less solid waste with rising trade.

Overall, our estimation results provide evidence that rising economic complexity and trade openness have a significant negative impact on the amount of solid waste generated per person per day in the municipalities of the state of São Paulo. In line with the EKC concept, our estimates further confirm the existence of an inverted U-shaped relationship between solid waste generation and economic development. The turning point, i.e. the level of per capita income at which the detrimental effect of economic development on the environment reverses, lies between 59,120 and 61,499 constant 2000 Brazilian Reais. These values lie within the income per capita range in our sample (see Table 9 in the Appendix).

4.2 Deforestation

Table 2 reports the first differences estimates for our analysis on the relationship between deforestation and economic complexity in municipalities in the Amazon basin region between 2002 and 2014. We find no evidence of a relationship between economic complexity and deforestation. Our estimates provide evidence, instead, for an inverted U-shaped relationship between deforestation rates and economic development. GDP per capita and its square term yield statistically significant estimates in all specifications. Deforestation rates soar with rising income per capita, but this

Table 2 Deforestation (first differences estimation)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: deforestation rate					
ECI	−0.392	1.661	1.724	2.783	2.344	2.328
	(2.079)	(3.038)	(3.053)	(2.933)	(3.678)	(3.662)
$(\text{ECI})^2$	0.0710					
	(0.0585)					
GDP p.c.		3.125***	3.135***	1.183	3.210***	3.098***
		(0.979)	(0.980)	(0.716)	(1.098)	(1.040)
$(\text{GDP p.c.})^2$		−0.0235***	−0.0236***	−0.0122	−0.0240**	−0.0234***
		(0.00873)	(0.00874)	(0.00947)	(0.00933)	(0.00901)
Population density			0.0628**			
			(0.0298)			
Trade openness				−0.584		
				(0.728)		
Harvested area					−3.28e−05	
					(1.27e−04)	
Planted area						2.08e−05
						(1.07e−05)
Cattle density	–					
	–					

(continued)

Table 2 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: deforestation rate					
Constant	−4.630***	−7.006***	−7.067***	−5.182***	−7.154***	−7.243***
	(0.605)	(1.010)	(1.019)	(1.267)	(1.026)	(1.039)
Observations	2194	1448	1448	551	1408	1408
R-squared	0.000	0.006	0.006	0.003	0.006	0.006
Adjusted R-squared	−0.000899	0.00399	0.00338	−0.00463	0.00330	0.00328

	(7)	(8)	(9)	(10)	(11)
	Dependent variable: deforestation rate				
ECI	0.814	1.676	1.674	1.657	1.653
	(3.255)	(4.464)	(4.463)	(4.519)	(4.519)
$(\mathrm{ECI})^2$				0.0757	0.0776
				(0.287)	(0.288)
GDP p.c.	5.319***	5.804***	5.787***	5.801***	5.785***
	(1.377)	(1.561)	(1.554)	(1.562)	(1.555)
$(\mathrm{GDP\ p.c.})^2$	−0.0398***	−0.0428***	−0.0427***	−0.0428***	−0.0427***
	(0.0123)	(0.0132)	(0.0131)	(0.0132)	(0.0131)
Population density		0.122	0.121	0.121	0.120
		(0.248)	(0.248)	(0.250)	(0.249)
Trade openness	–				
	–				

(continued)

Table 2 (continued)

	(7)	(8)	(9)	(10)	(11)
	Dependent variable: deforestation rate				
Harvested area		−1.43e−04		−1.43e−04	
		(1.26e−04)		(1.26e−04)	
Planted area			−0.000137		−0.000137
			(1.25e−04)		(1.25e−04)
Cattle density	−0.300	−0.293	−0.294	−0.293	−0.294
	(0.239)	(0.243)	(0.243)	(0.243)	(0.243)
Constant	−8.012***	−8.008***	−8.025***	−8.017***	−8.034***
	(1.435)	(1.444)	(1.443)	(1.452)	(1.451)
Observations	888	862	862	862	862
R-squared	0.011	0.012	0.012	0.012	0.012
Adjusted R-squared	0.00702	0.00514	0.00510	0.00398	0.00394

Notes Standard errors, in parentheses, are clustered at the municipality-level. All variables are first-differenced. *Interpretation* ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

trend reverses when a certain income threshold is reached. The turning points for income per capita lie between 48,585 and 66,810 constant 2000 Brazilian Reais, thus well within the range (cf. Table 10).

Included individually, the coefficient on population density is statistically significant with a positive sign, confirming our expectation that deforestation is more acute in densely populated areas. Nevertheless, the estimate turns out to be insignificant when including additional control variables.

4.3 Forest Fires

Table 3 reports the first differences estimates for our analysis on the relationship between forest fires and economic complexity in Brazilian states and the federal district between 2002 and 2009. As in Sects. 4.1 and 4.2, neither the ECI nor its square term are significantly different from zero in the baseline specification. The ECI estimate turns significant in specifications (6), (10), (11) and (12), suggesting a linear and positive correlation between forest fires and economic complexity. In other words, the number of forest fires rises with economic complexity. This can be ascribed to the fact that rising economic complexity is likely to call for a more efficient use of the land. Forest fires could be an easy way to clear the land for new activities.

Further, there is robust evidence for an inverted U-shape relationship between forest fires and per capita income. The square term of GDP per capita is significant in all specifications and bears a negative sign. In line with the EKC hypothesis, this implies that the number of observed forest fires in Brazilian states first increases with rising incomes, but levels off and starts declining at a certain GDP per capita value. This is because economic development is accompanied by a growing demand for environmental quality, which will render the regulatory framework limiting forest fires more effective.

Additionally, forest fires are significantly and negatively associated with trade openness, a finding that stands firm to the inclusion of multiple variables. All things equal, the number of annually observed heat sources in Brazilian states hence decreases with intensified trade. There is also evidence that the number of forest fires decreases with more hectares planted. While the sign of this estimate seems odd at first sight, if plantation accounts for reforestation as well, this might be an indication that Brazil’s current sustainable reforestation projects are yielding the desired outcomes (cf. Goldenberg and Roberts 2015).

In order to test the robustness of our findings, we run regressions (1)–(12) on a subsample which does not comprise the state of São Paulo (unpublished results). São Paulo accounts for ECI values more than ten times higher than the other Brazilian states. Excluding this state confirms our findings from the full sample analysis with respect to economic complexity and trade openness. In the subsample analysis forest fires increase linearly with GDP per capita. This finding is not surprising when the

Table 3 Forest fires (first differences estimation)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: forest fires					
ECI	287.7	419.1	415.4	418.5	413.2	430.2*
	(247.0)	(253.3)	(248.8)	(245.5)	(251.1)	(252.2)
$(\mathrm{ECI})^2$	−0.752					
	(0.811)					
GDP p.c.		7929**	8640***	8228**	7475**	7800**
		(2903)	(3046)	(3046)	(2821)	(2903)
$(\text{GDP p.c.})^2$		−65.04**	−80.66**	−68.93**	−61.28**	−63.05**
		(25.83)	(35.26)	(27.66)	(24.72)	(26.23)
Population density			168.9			
			(180.8)			
Urbanisation				−133.8		
				(651.1)		
Trade openness					−12,401*	
					(7174)	
Average education						−4421
						(3363)
Higher education	–					
	–					

(continued)

Table 3 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: forest fires					
Harvested area	–					
	–					
Planted area						
	–					
Cattle density	–					
	–					
Constant	−620.7	−2694***	−2927***	−2737***	−2327***	−2001**
	(377.1)	(945.2)	(1024)	(946.1)	(834.7)	(774.9)
Observations	189	189	189	177	189	189
R-squared	0.008	0.119	0.120	0.126	0.122	0.127
Adjusted R-squared	−0.00309	0.104	0.101	0.105	0.103	0.108

	(7)	(8)	(9)	(10)	(11)	(12)
	Dependent variable: forest fires					
ECI	421.5	410.5	423.2	477.1*	618.3***	614.5***
	(252.4)	(249.5)	(251.6)	(248.0)	(203.5)	(206.2)
$(ECI)^2$						0.211
						(1.270)
GDP p.c.	7834**	8291**	8289**	9471***	13,537***	13,481***

(continued)

Table 3 (continued)

	(7)	(8)	(9)	(10)	(11)	(12)
	Dependent variable: forest fires					
	(2899)	(3357)	(3337)	(3227)	(4773)	(4808)
$(\text{GDP p.c.})^2$	−63.28**	−68.47**	−68.63**	−78.80**	−118.3*	−116.7*
	(26.26)	(29.51)	(29.46)	(29.96)	(57.85)	(61.90)
Population density					−54.69	−68.77
					(350.9)	(414.7)
Urbanisation					493.6	496.8
					(568.1)	(580.6)
Trade openness					−304,53**	−304,48**
					(127,224)	(127,993)
Average education					−7783	−7771
					(6757)	(6754)
Higher education	−356.4					
	(468.2)					
Harvested area		−0.00192				
		(0.00182)				
Planted area			−0.00237		−0.00454*	−0.00456*
			(0.00191)		(0.00251)	(0.00254)
Cattle density				−70.50	−885.6	−886.6
				(437.2)	(610.4)	(617.1)

(continued)

Table 3 (continued)

	(7)	(8)	(9)	(10)	(11)	(12)
	Dependent variable: forest fires					
Constant	−2281***	−2668***	−2641***	−2607**	−970.4	−959.0
	(778.1)	(953.5)	(939.4)	(1165)	(1742)	(1791)
Observations	189	189	189	135	123	123
R-squared	0.121	0.121	0.122	0.155	0.220	0.220
Adjusted R-squared	0.102	0.102	0.103	0.129	0.158	0.150

Notes Standard errors, in parentheses, are clustered at the state-level. All variables are first-differenced. *Interpretation* ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

turning points of the full sample regressions are taken into account. The turning points are higher than the maximum income per capita recorded in the panel of ca. 55,000 constant 2010 Brazilian Reais (cf. Table 11). The highest turning point amounts to 62,231 Brazilian Reais and lies well outside the range. Reaching an income that allows to reverse the detrimental effect of growth on the environment is hence unrealistic, leaving the states in the upward sloping part of the EKC.

4.4 Air Pollution

Our last set of regressions examines the relationship between air pollution and economic complexity in Brazilian metropolitan regions from 2002 to 2009. In total, we analyse ten different indicators of air pollution: maximum and average concentrations of sulphur dioxide, nitrogen dioxide, TSP and ultrafine particles, as well as maximum concentrations of carbon monoxide and ozone. For most of these indicators the models were poorly specified and over-parameterised because of a low number of observations. Therefore, we give more emphasis to two air pollution indicators: maximum concentration of carbon monoxide, and maximum concentration of ozone. Tables 4 and 5 show that, neither economic complexity nor income per capita have a statistically significant impact on these air pollutants. In the case of ozone, population density has a robust and statistically significant impact on maximum concentrations. These concentrations decrease in more densely populated metropolitan regions, probably due to higher industrialisation standards providing cleaner technologies and enhanced environmental awareness on the part of their inhabitants. The other control variables have no robust impact on carbon monoxide or ozone concentrations. Finally, Tables 6 and 7 show some indication of a negative impact from ECI to air pollution and a positive impact from GDP per capita to air pollution. These results should be read with cautions given the low number of observations.

5 Conclusion

This paper investigates the extent to which economic complexity affects the environment in Brazil. We hypothesize that environmental degradation rises as economies diversify their production and become more complex, but an eventual structural change towards knowledge-intensive industries creates the technology necessary to limit degradation. Using panel data regression techniques and a rich set of control variables, we analyse the relationship between economic complexity and solid waste generation, deforestation, forest fires and air pollution. We find that waste generation decreases, but forest fires increase linearly with rising complexity. Economic complexity has no robust, if any, impact on deforestation or air pollution. In line with the traditional EKC, whereby degradation first increases and subsequently decreases

Table 4 Maximum carbon monoxide concentrations (fixed effects estimation)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable: maximum carbon dioxide concentrations									
ECI	−0.0651	0.361	0.303	0.368	0.393	0.382	0.380	0.386	0.449	0.183
	(0.152)	(0.442)	(0.306)	(0.437)	(0.359)	(0.246)	(0.291)	(0.238)	(0.272)	(0.197)
$(\text{ECI})^2$	0.456									0.302
	(0.292)									(0.340)
GDP p.c.		−6.223	−1.059	−1.886	−1.028	0.187	−0.559	0.378	0.747	−0.156
		(9.626)	(0.716)	(1.051)	(0.809)	(0.745)	(0.692)	(0.865)	(1.175)	(12.99)
$(\text{GDP p.c.})^2$		10.20								1.332
		(23.66)								(31.91)
Population density			−2.175						2.099	1.444
			(1.404)						(2.731)	(1.655)
Urbanisation				0.113					−0.0683	0.0932
				(0.384)					(0.471)	(0.798)
Trade openness					−0.190**			−0.0365	−0.0172	−0.0546
					(0.0586)			(0.159)	(0.151)	(0.148)
Year						−0.0738**		−0.0973	−0.136	−0.107
						(0.0227)		(0.0799)	(0.0909)	(0.0956)
							−0.0327*	0.0156	0.0130	0.0143
Higher education							(0.0131)	(0.0277)	(0.0319)	(0.0307)

(continued)

Table 4 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable: maximum carbon dioxide concentrations									
Constant	8.671***	14.67***	25.59**	12.74***	10.93***	156.4**	11.65***	202.2	266.5	212.5
	(0.230)	(3.014)	(9.564)	(1.564)	(1.728)	(44.87)	(1.590)	(157.9)	(173.2)	(186.0)
Observations	54	46	46	46	46	46	46	46	46	46
# of metropolitan regions	7	6	6	6	6	6	6	6	6	6
R-squared	0.103	0.136	0.172	0.133	0.169	0.219	0.198	0.223	0.231	0.253
Adjusted R-squared	0.068	0.0744	0.113	0.0714	0.11	0.163	0.14	0.125	0.0899	0.0662

Notes Standard errors, in parentheses, are clustered at the metropolitan region-level. We use the natural logarithm of all variables, except for the ECI, its square term, and the share of total economically active population which has attended higher education. *Interpretation* ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 5 Maximum ozone concentrations (fixed effects estimation)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent variable: maximum ozone concentrations								
ECI	0.137	0.379	0.28	0.336	0.384	0.381	0.377	0.084	−0.226
	(0.157)	(0.463)	(0.270)	(0.415)	(0.450)	(0.416)	(0.456)	(0.339)	(0.351)
$(\text{ECI})^2$	0.285								0.303*
	(0.168)								(0.146)
GDP p.c.		12.98	1.092	0.206	0.144	0.579	0.143	−0.268	−9.402
		(21.66)	(1.119)	(1.400)	(1.548)	(0.933)	(0.970)	(2.209)	(22.78)
$(\text{GDP p.c.})^2$		−30.50							20.41
		(53.64)							(58.10)
Population density			−3.398**					−8.768**	−10.39***
			(1.226)					(3.009)	(2.487)
Urbanisation				−0.789				−0.248	−0.216
				(1.086)				(0.784)	(0.511)
Trade openness					−0.0632			−0.0286	−0.0475
					(0.0901)			(0.150)	(0.102)
Year						−0.0257		0.0580	0.0862
						(0.0257)		(0.0873)	(0.112)
Higher education							−0.00688	0.0490	0.0599
							(0.0168)	(0.0562)	(0.0803)

(continued)

Table 5 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent variable: maximum ozone concentrations								
Constant	5.042***	0.618	25.05**	7.620	4.751	55.34	5.164	−54.21	−96.71
	(0.185)	(5.845)	(9.602)	(6.190)	(3.363)	(52.82)	(2.726)	(166.5)	(233.3)
Observations	54	46	46	46	46	46	46	46	46
# of metropolitan regions	7	6	6	6	6	6	6	6	6
R-squared	0.063	0.070	0.122	0.080	0.047	0.052	0.046	0.223	0.249
Adjusted R-squared	0.0262	0.00389	0.0593	0.0141	−0.0211	−0.0154	−0.0221	0.0793	0.0613

Notes Standard errors, in parentheses, are clustered at the metropolitan region-level. We use the natural logarithm of all variables, except for the ECI, its square term, and the share of total economically active population which has attended higher education. *Interpretation* ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 6 Average total suspended particle concentrations (fixed effects estimation)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable: average TSP concentrations									
ECI	−0.149**	−0.112*	0.00745	−0.147*	−0.0196	0.0481	−0.0163	0.00259	−0.0983	−0.140
	(0.0543)	(0.0506)	(0.0435)	(0.0489)	(0.110)	(0.0745)	(0.0507)	(0.0772)	(0.0828)	(0.0851)
$(\text{ECI})^2$	−0.00885									0.0999
	(0.0575)									(0.0462)
GDP p.c.		0.319	3.726**	6.377**	3.882	2.521	5.752***	4.845**	4.063**	4.292**
		(4.012)	(1.002)	(1.268)	(2.812)	(3.646)	(0.320)	(0.857)	(1.139)	(1.243)
$(\text{GDP p.c.})^2$		−3.893	−8.842**	−16.77**	−10.32	−5.394	−13.21***	−11.39**	−12.04**	−12.43**
		(9.110)	(2.241)	(2.921)	(5.464)	(7.962)	(0.719)	(2.579)	(3.010)	(3.069)
Population density			−3.852***					−3.644*	−6.651*	−7.051*
			(0.707)					(1.444)	(2.487)	(2.382)
Urbanisation				0.648**				0.106	0.520	0.539
				(0.151)				(0.245)	(0.382)	(0.379)
Trade openness					−0.190				−0.107	−0.122
					(0.218)				(0.126)	(0.118)
Year						−0.0567			0.118	0.120
						(0.0340)			(0.115)	(0.109)
							−0.0235		−0.0209	−0.0184
Higher education							(0.0154)		(0.0328)	(0.0313)

(continued)

Table 6 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable: average TSP concentrations									
Constant	4.343***	7.094**	28.12***	1.051	3.642	116.7	3.022***	27.87*	−186.2	−187.5
	(0.0448)	(2.188)	(3.997)	(0.949)	(2.929)	(66.24)	(0.214)	(10.58)	(210.4)	(199.8)
Observations	42	34	34	28	34	34	28	28	28	28
# of metropolitan regions	6	5	5	4	5	5	4	4	4	4
R-squared	0.026	0.136	0.313	0.405	0.210	0.204	0.502	0.682	0.747	0.763
Adjusted R-squared	−0.0244	0.0492	0.219	0.302	0.100	0.0946	0.415	0.610	0.641	0.645

Notes Standard errors, in parentheses, are clustered at the metropolitan region-level. We use the natural logarithm of all variables, except for the ECI, its square term, and the share of total economically active population which has attended higher education. *Interpretation*: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7 Average ultrafine particle concentrations (first differences estimation)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: average PM10 concentrations							
ECI	−0.0540	−0.0587	−0.0734	−0.0122	−0.0745*	−0.0775	−0.0164	0.0251
	(0.0448)	(0.0314)	(0.0422)	(0.0364)	(0.0366)	(0.0393)	(0.0395)	(0.0376)
$(\text{ECI})^2$	−0.0124							−0.0396
	(0.0495)							(0.0397)
GDP p.c.		7.525	1.026**	1.492**	1.205***	1.222***	1.715*	7.427
		(5.725)	(0.258)	(0.417)	(0.212)	(0.201)	(0.837)	(7.125)
$(\text{GDP p.c.})^2$		−14.57						−13.01
		(12.84)						(15.32)
Population density			−1.222				0.584	1.202
			(1.439)				(1.498)	(2.351)
Urbanisation				−0.493**			−0.543	−0.553
				(0.171)			(0.297)	(0.280)
Trade openness					−0.0196		0.0380	0.0423
					(0.0424)		(0.0769)	(0.0769)
Year						7.48e−05	0.00837	0.00790
						(0.0191)	(0.0327)	(0.0318)
Higher education								

(continued)

Table 7 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: average PM10 concentrations							
Constant	−0.0206	−0.0510*	−0.0279	−0.0587**	−0.0456	−0.0492	−0.0912	−0.103
	(0.0183)	(0.0213)	(0.0267)	(0.0198)	(0.0241)	(0.0427)	(0.0867)	(0.0842)
Observations	39	32	32	32	32	32	32	32
R-squared	0.009	0.121	0.115	0.225	0.107	0.106	0.231	0.245
Adjusted R-squared	−0.0457	0.0272	0.0199	0.142	0.0110	0.00983	0.0459	−0.0177

Notes Standard errors, in parentheses, are clustered at the metropolitan region-level. All variables are first-differenced. We use the natural logarithm of all variables, except for the ECI, its square term, and the share of total economically active population which has attended higher education. *Interpretation* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

with income, we find a non-linear relationship between economic development and waste generation and deforestation.

Being the first study to investigate the environment-complexity nexus for Brazil, it leaves scope for improvement and extension. The quality and quantity of Brazilian data as well as the access to it should be enhanced and facilitated. Moreover, our study can possibly be extended by time series analyses on individual municipalities or states. Notwithstanding these considerations, our study sheds first light on the compelling relevance of economic complexity as a potential additional driver of environmental degradation. To that extent, our paper is also novel since such a relationship has not been analysed in other academic papers. By looking at economic complexity we pay specific attention to the structure of the economy. Nonetheless, the impact of economic complexity and technological progress on environmental quality cannot easily be separated from environmental policies. As Jaffe et al. (2003) argue, well-designed environmental policies can contribute to technological innovation and dissemination and can help maintain (or create) a high standard of living. There is a strong need for Brazil to develop and conciliate specific national and local industrial and environmental policies to increase the economic complexity of its industries and create growth in a sustainable way by protecting the environment.

Appendix

Data Sources

Table 8 contains the sources of all the data employed in our study. This includes both data of variables included in the regressions, and data of variables used to construct or transform variables that could not be found in the necessary disaggregation level. The variables are listed in alphabetical order.

Descriptive Statistics

Tables 9, 10, 11 and 12 provide descriptive statistics for our five panels. Since we find robust evidence for inverted U-shaped relationships between income per capita and solid waste generation, deforestation and forest fires in Sect. 4, the statistics on income per capita are needed to determine whether the turning points of the EKCs lie within the range.

Table 8 Data sources

Variable	Unit	Disaggregation level	Source
Air pollution indicators (average concentrations)	Microgram per cubic meter	Metropolitan region	IBGE
Air pollution indicators (maximal concentrations)	Microgram per cubic meter	Metropolitan region	IBGE
Area	Square kilometre	State, metropolitan region, municipality	IPEA, PRODES (INPE)
Average years of education	Units	State	IPEA
Cattle	Units	State, municipality	IPEA
Cattle density	Units per square kilometer	State, municipality	Constructed with IPEA Data
Deflator	Annual percentage	United States of America	World Bank
Deforestation rates	Square kilometers	Municipality	PRODES (INPE)
Domestic solid waste Generation	Tons per day	Municipality (state of São Paulo)	CETESB
Domestic solid waste generation per capita	Kilograms per day per person	Municipality (state of São Paulo)	Constructed with IPEA and CETESB data
ECI	Index	State, municipality	SECEX/MCID
ECI	Index	Metropolitan region	Constructed with SECEX/MCID data
Exchange rate	USD-BRL	Brazil	IMF
Export volume	Current USD	State, municipality	UN Comtrade
Export volume	Current USD	Metropolitan region	Constructed with UN Comtrade data

(continued)

Table 8 (continued)

Variable	Unit	Disaggregation level	Source
Export volume	Constant 2010 BRL	State	Constructed with UN Comtrade, IMF and World Bank data
Export volume	Constant 2000 BRL	Metropolitan region, municipality	Constructed with UN Comtrade, IMF and World Bank data
Forest fires	Number of heat sources	State	IBGE
GDP	Constant 2010 BRL	State	IPEA
GDP	Constant 2000 BRL	Metropolitan region, municipality	IPEA
GDP per capita	Constant 2010 BRL	State	IPEA
GDP per capita	Constant 2000 BRL	Metropolitan region, municipality	Constructed with IPEA data
Import volume	Current USD	State, municipality	UN Comtrade
Import volume	Current USD	Metropolitan region	Constructed with UN Comtrade data
Import volume	Constant 2010 BRL	State	Constructed with UN Comtrade, IMF and World Bank data
Import volume	Constant 2000 BRL	Metropolitan region, municipality	Constructed with UN Comtrade, IMF and World Bank data
Population density	Inhabitants per square kilometer	State, metropolitan region, municipality	Constructed with IPEA (and PRODES) data
Rural population	1000 inhabitants	State, metropolitan region	IBGE
Share of individuals with low/intermediary/high education	Percentage	State, metropolitan region	Constructed with IBGE data

(continued)

Table 8 (continued)

Variable	Unit	Disaggregation level	Source
Trade openness ratio		State, metropolitan region, municipality	Constructed with IPEA, UN Comtrade, IMF and World Bank data
Total harvested area	Hectares	State, municipality	IPEA
Total planted area	Hectares	State, municipality	IPEA
Urban population	1,000 inhabitants	State, metropolitan region	IBGE
Urban-to-rural-population ratio		State, metropolitan region	Constructed with IBGE data

Abbreviations CETESB (Companhia Ambiental do Estado de São Paulo); IBGE (Instituto Brasileiro de Geografia e Estatística); IMF (International Monetary Fund); INPE (Instituto Nacional de Pesquisas Espaciais); IPEA (Instituto de Pesquisa Econômica Aplicada); SECEX/MDIC (Secretaria de Comércio Exterior/Ministério da Indústria, Comércio Exterior e Serviços); UN Comtrade (United Nations Commodity Trade Statistics Database)

Table 9 Descriptive statistics

Variables	N	Mean	SD	Min.	Max.
Waste generation p.c.	5805	0.350	0.135	0.0182	4.320
ECI	3169	0.381	1.582	−4.652	19.41
$(\text{ECI})^2$	3169	2.647	16.36	0	376.8
Trade openness	2253	0.483	1.319	5.02e−05	29.49
GDP p.c.	5160	8.153	7.342	1.867	115.6
$(\text{GDP p.c.})^2$	5160	120.4	451.1	3.487	13,368
Population density	5805	299.2	1190	3.714	12,956

Panel: solid waste generation

Table 10 Descriptive statistics

Variables	N	Mean	SD	Min.	Max.
Deforestation rate	9880	17.85	59.40	0	1408
ECI	2622	−0.125	0.805	−8.223	9.972
$(\text{ECI})^2$	2622	0.663	5.535	0	99.44
GDP p.c.	6832	4.255	5.308	0.743	84.49
$(\text{GDP p.c.})^2$	6832	46.27	252.3	0.552	7139
Population density	9874	23.08	124.9	0.0736	2732
Trade openness	763	0.533	1.269	0.000307	18.04
Harvested area	6765	15,762	52,826	8	847,884
Planted area	6765	15,997	53,433	8	875,851
Cattle density	4533	33.20	35.74	0.000564	247.8

Panel: deforestation

Table 11 Descriptive statistics

Variables	N	Mean	SD	Min.	Max.
Forest fires	216	7632	12,746	36	75,548
ECI	216	0.650	29.51	−29.26	153.6
$(\text{ECI})^2$	216	867.1	4091	7.54e−06	23,591
GDP p.c.	216	14.49	9.172	4.953	55.15
$(\text{GDP p.c.})^2$	216	293.6	501.8	24.54	3041
Population density	216	64.76	97.82	1.548	449.3
Urbanisation	204	5.674	6.322	1.355	30.16
Trade openness	216	0.0631	0.0793	0.00122	0.471
Average education	216	6.247	1.119	3.982	9.643
Higher education	216	20.61	5.803	8.070	39.24
Harvested area	216	2.256e+06	2.740e+06	12,726	9.998e+06
Planted area	216	2.297e+06	2.769e+06	13,687	1.007e+07
Cattle density	162	29.06	18.64	0.570	69.96

Panel: forest fires

Table 12 Descriptive statistics

Variables	N	Mean	SD	Min.	Max.
Sulphur dioxide (avg. concentration)	54	9.037	4.829	0	25
Sulphur dioxide (max. concentration)	59	148.8	229.4	14	1395
Nitrogen dioxide (avg. concentration)	47	34.13	17.84	7	83
Nitrogen dioxide (max. concentration)	52	261.1	142.0	82	716
TSP (avg. concentration)	42	88.36	70.83	36	328
TSP (max. concentration)	43	380.7	287.3	89	1379
PM10 (avg. concentration)	47	34.34	13.69	16	72
PM10 (max. concentration)	54	167.5	71.13	59	420
Carbon monoxide (max. concentration)	54	8571	3515	3557	21,641
Ozone (max. concentration)	54	228.7	149.7	97	1081
ECI	72	0.292	0.700	−0.621	2.104
$(\mathrm{ECI})^2$	72	0.568	1.223	1.12e−06	4.428
GDP p.c.	64	11.28	4.784	5.386	24.36
$(\mathrm{GDP\ p.c.})^2$	64	149.9	142.2	29.01	593.3
Population density	64	953.3	856.2	38.73	2489
Urbanisation	56	56.36	45.09	9.419	161.0
Trade openness	72	0.399	0.411	0.0192	2.468
Higher education	56	47.97	4.758	39.51	58.43

Panel: air pollution

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