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150 Years of Italian CO_2 Emissions and Economic Growth*

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Abstract

This paper examines the relationship between economic growth and carbon dioxide emissions in Italy considering the developments in a 150-year time span. Using several statistical techniques, we find that GDP growth and carbon dioxide emissions are strongly interrelated, with a dramatic change of the elasticity of pollutant emissions with respect to output. Our findings highlight lack of structural change in the reduction of the carbon dioxide, suggesting the difficulties for Italy to meet the emissions targets within the Europe 2020 strategy.

Keywords: Carbon Dioxide Emissions, Time Series Analysis, Italian Economy, Environmental Kuznets Curve.
JEL classification: Q50, C22.

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1 Introduction

Environmental awareness has become a central issue in the policy debate, and in particular the transition towards a low-carbon economy has represented one of the major economic challenges. In this context the realization of the Europe 2020 strategy for sustainable economic growth relies on the use of sustainable energy sources, having three main headline targets, that is (i) drastic cutting down of the carbon dioxide (CO_2) emissions, (ii) increasing the share of renewable energy sources in final energy consumption, and (iii) increasing energy efficiency. This set of EU-level goals have been translated into national objectives by each member state taking into account country-specific economic circumstances. Over the last decades Italy has made a unilateral commitment to reduce overall greenhouse gas emissions by 13% compared to 1990 levels, increase the share of renewable energy sources in final energy consumption to 17% and cut energy consumption by 27.90 mtoe (mega tons of oil equivalent) always with reference to 1990 levels.

In this paper we examine the relationship between economic growth and carbon dioxide emissions in Italy for a period which goes from the unification, 1861, up to 2011. To this end we adopt the most recent statistical reconstruction of the GDP series for the last 150 years.[1] After a period of prolonged low growth, the Italian economy has recently found itself at the center of a deep economic crisis. By adopting an intensive reform agenda which has promoted more competition, and then economic growth, Italy was able to manage the recent financial crisis. However, further economic challenges are needed, facing further action to strengthen its growth prospects, see, e.g. Annicchiarico, Di Dio, and Felici (2013); European Council (2012). In this economic scene, the environmental policy debate has been put aside and Italy has not yet clearly articulated its future energy strategies, even though greenhouse gases (GHG) emissions are largely derived from energy-related

[1] The GDP series has been part of a study published on occasion of the recent celebrations of the 150th anniversary of the unification of Italy; for more details, see Baffigi (2011); Vecchi (2011).

activities (OECD, 2012). The recent economic events represent an opportunity for Italy to restructure its economy looking at other alternative sources to satisfy its energy needs. In particular, Italy has limited domestic energy resources with high dependence on external energy supply, and so an energy import dependency of 83.8% in 2010 against a EU-27 of 52.7%, see European Council (2012). Since 1990 final energy consumption has been increasing steadily, with transport, households and industry being the most energy-consuming sectors.[2] Italian per capita CO_2 emissions are well below the EU-27 average. However, the energy intensity in Italy is lower than the EU-27 average, but the carbon dioxide emissions are above the EU-27 mean level.[3] In particular, the Italian oil and gas shares in primary energy supply are above the European average, while hydroelectricity and other renewable sources still play a minor role.[4] Given this scenario, it appears clear the need for Italy to start investing in a significant reduction of CO_2 emissions as a priority, before implementing new environmental policy interventions.[5]

With this analysis we contribute to the literature which studies the relationship between carbon dioxide emissions and economic activity by using different but complementary statistical approaches, having as a focus the investigation of the economic trend and conditions of the Italian economy. Italy has been often analyzed within a panel of countries (Galeotti, Lanza, and Pauli, 2006; Richmond and Kaufmann,

[2]In 2010, probably as a consequence of the strong slowdown of the economy, the households sector consumed more energy than the industry sector (25.2% against 24.9%, while the transport sector absorbed 33.6% of the total final energy consumption). See European Council (2012).

[3]In 2009 Italian carbon dioxide emissions per capita were equal to 7,200.8 kg /cap, while the EU-27 level was 8,105 kg/cap; the Italian CO_2 intensity was 2,549.9 kg CO_2/toe , while the average in the EU was equal to 2,381 kg CO_2/toe. Always in 2010 energy intensity in Italy was 123.6 toe/MEUR '05 (compared to 152.3 toe/MEUR '05 of the EU-27 average). For more details see European Commission (2012).

[4]In 2010 gross electricity generation in Italy is attributable to gases (52.1%), renewable sources (26.6%), solid fuels (13.2%), petroleum products (7.2%). In EU-27, in the same year, gross electricity generation is imputable to nuclear (27.4%), solid fuels (24.7%), gases (23.6%), renewable sources (20.9%), petroleum products (2.6%). In 2010 the energy gross inland consumption of Italy by product is so distributed: petroleum products (40.2%), gases (38.8%), renewables (10.3%), solid fuels (8.1%), waste (0.5%); in EU-27 energy gross inland consumption by product is due to petroleum products (35.1%), gases (25.1%), solid fuels (15.9%), nuclear (13.4%), renewables (9.8%), waste (0.6%). See European Commission (2012).

[5]For further details about energy policy in Italy, see International Energy Agency (2009).

2006; Martínez-Zarzoso and Bengochea-Morancho, 2004; Dijkgraaf and Vollebergh, 2005, *inter alia*). However, a more precise investigation of the relationship between economic growth and environment effects requires the study of the single country characteristics underlying the importance of the specific historical experience (de Bruyn, van der Bergh, and Opschoor, 1998; Stern, 1998a,b; Dijkgraaf and Vollebergh, 2005). Moreover, many studies where Italy has been included rely on linear cointegration techniques, while a nonlinear cointegration approach is recommended, see Hong and Wagner (2008).

To disentangle the effects of economic growth on carbon dioxide and emissions we adopt different approaches. Initially we study the time series properties testing for stationarity, and the existence of unit roots along with a Cointegrated VAR (CVAR or "restricted VAR") model by following the Juselius (2006) empirical approach. Subsequently, we consider a nonlinear representation of the same model by investigating whether and when nonlinear behavior arise in our observed variables. More specifically, we study whether Italy has shown any transition between regimes, i.e. low emissions, high emissions, estimating a Smooth Transition Autoregressive (STAR) model for a univariate scenario (Chan and Tong, 1986; Teräsvirta, 1994; van Dijk, Teräsvirta, and Franses, 2002; Teräsvirta, Tjøstheim, and Granger, 2010). With this target we use the multiple-regime STAR version introduced by Franses and van Dijk (1999) (MR-STAR) to test if radical changes affect the data, estimating the regimes transitions. The same problem is also considered in a multivariate context, under the assumption that the regime switching is unobserved. For this latter approach we adopt a simple Markov-Switching VAR (MS-VAR).[6] For our analysis we are interested to identify the phases of recession versus expansion for GDP, and the high versus the low rates of emissions for CO_2. Finally, to complete the investigation, we test for the Environmental Kuznets Curve (EKC) hypothesis, according

[6]This family of time series models have been introduced in econometrics by Hamilton (1989), in order to check if, and eventually when, the series under investigation can be described by two different unobserved regimes.

to which environmental degradation tends to increase as the economy develops, but begins to decline at higher levels of income (Grossman and Krueger, 1993, 1995; Stern, 1998a,b; Müller-Fürstenberger and Wagner, 2004; Selden and Song, 1994, *inter alia*).

Our results suggest that real GDP and carbon dioxide emissions are strongly interrelated, and the behavior of emission intensity defined as CO_2 emissions to GDP ratio is highly nonlinear. In particular, the CVAR analysis shows evidence of a common trend between real GDP and CO_2, which changes direction, globally increasing before 1975, and decreasing after that year. This could be probably due to the energy efficiency policies implemented in the aftermath of the oil crises of the 1970s. Consistently, the MR-STAR analysis suggests the presence of two structural shocks in 1881-1891 decade and in the second half of the Seventies. The MS-VAR analysis seems to be more sensitive to the non-structural shocks, as shown by the change in regime after the post World Wars periods. In addition, according to this analysis the post-1975 reverse trend in CO_2 emissions seems less evident, resulting instead in a non-structural shock, while the state of high growth/high pollution appears to be permanent until the 2008 financial crisis. The results of the MS-VAR analysis would then suggest that no structural change in the reduction of the CO_2 emissions has been implemented. Finally, our results on the EKC confirm that real GDP and carbon dioxide emissions are strongly interrelated and a sort of bell-shaped relationship seems to be present. However, the predicted turning point is at a very high level of per capita GDP. It may be due to the rigid structure of the standard quadratic EKC which shows to be outperformed by the flexible structure allowed by a cubic piecewise model.

The rest of the paper is organized as follows. In Section 2 we describe the dataset and discuss the historical evolution of carbon dioxide emissions and GDP in Italy. In Section 3 we study the properties of the time series by testing for unit roots and stationarity. The results on cointegration, structural change and non-linearities are presented in Section 4, and in Section 5 we estimate a standard EKC model for carbon dioxide emissions. The main conclusions of the analysis are summarized in Section 6.

2 Data and Time Series Properties

To study the time evolution of the carbon dioxide emissions for Italy, we use annual data on total fossil fuel CO_2 emissions, real GDP and total population for the time period 1861-2011. Data on carbon dioxide emissions, stemming from fossil-fuel burning and the manufacture of cement, are from the database of the Carbon Dioxide Information and Analysis Center (CDIAC), provided by the Earth Sciences Division of the Oak Ridge National Laboratory which provides full information on the CO_2 emissions expressed in thousand metric tons of carbon.[7] The current dataset covers the period 1861-2009, while for the years 2010-2011 the CDIAC provides preliminary estimates obtained by extrapolation.[8]

For the 1861-2011 data on GDP we apply the most recent statistics based on the reconstruction of the national accounts, which is the result of a recent project coordinated by the Bank of Italy in cooperation with ISTAT, and University of Rome "Tor Vergata", see Baffigi (2011); Vecchi (2011) for full details. Notice that the GDP series is expressed in million of euros at 2005 constant prices, and from the same sources we extract data on population.

In Figures 1-4 we plot the historical patterns of GDP, and carbon dioxide emissions in Italy, for the period 1861-2011. More specifically, Figure 1 depicts the time series of per capita GDP for the whole period and for the two sub-samples 1861-1913 and 1950-2011. In line with the neutrality policy declared by Italy at the beginning of first global conflict (August 1914), the two sub-sample exclude the years 1914-1949 between the starting point of the World War I (WWI) and the years immediately

[7] The CDIAC maintains an extensive database on annual anthropogenic carbon dioxide emissions from each country, see Boden, Marland, and Andres (2012).

[8] See http://cdiac.ornl.gov/trends/emis/meth_reg.html for details.

after the World War II (WWII). During the 19th century the Italian economy was characterized by the presence of a large agricultural sector, which only at the end of the century gave way to an extensive industrialization. Indeed, although in Italy the industrial revolution began in the 1840s, only late in the 1890s modern infrastructures had begun to be built (Maddison, 2001; Malanima and Zamagni, 2010). Only at the end of the WWII following the economics reconstruction, Italy experienced an unprecedented period of rapid economic growth which was known as "economic miracle". The growth of the industrial output in the years from 1950 and 1974 drove a rise in per capita GDP to an average 5.3% per year, reaching a peak of 7.3% in 1961. In the early 70's due to the first oil crisis, the pace of growth slowed down causing a significant downturn of the Italian economy creating a wide economic disparities which caused in 1975 a drop in per-capita GDP of 2.7%. In the second half of the 1980s, the Italian economy was again prospering until the recession of the earlier 1990s. Over the last two decades Italy has been experiencing a prolonged period of slow growth with an average of 0.57% per annum. This poor performance, mainly due to a slowdown in the productivity, has been exacerbated by the recent crisis, see OECD (2012).

Figure 2 presents per capita carbon dioxide emissions for the whole sample and plots the series for the two sub-samples 1861-1913 and 1950-2011. At earlier stages of Italian economic development, we observe a slight increase in CO_2 emissions, and then two dramatic falls during the World Wars. From 1950 until the late 1970s, we notice a continuous, or even accelerating, growth of per capita CO_2 emissions. Immediately after the second oil shock in 1979, the growth of per capita CO_2 emissions with per capita gross domestic product levels out, as it emerges clearly from Figure 2c. This could be the result of the Italian economy's adjustment to the oil price shocks. Actually, the early 1980s saw some radical changes in the organization of Italian big industry with the introduction of automation and the dramatic reduction in the industrial work-force.[9] The recession in the early 1990s reduced the emissions slightly. From the second half of the 90's onwards there has been a constant, but slower, growth of carbon dioxide emissions amounting to around 2,228 kilos of carbon dioxide per capita in 2003. Since then we observe a decline up to 1,797 kilos of carbon dioxide per capita in 2011. Of course this sharp fall in emissions could be due to the recent crisis.

Figure 3 plots per capita carbon dioxide emissions against per-capita GDP, and as expected the period as a whole is characterized by a strong positive correlation between the two series.

Finally, Figure 4 reports the ratio between CO_2 emissions and GDP, expressed as CO_2 metric tons per million of euros. The CO_2/GDP ratio increases sharply from 1861, and then it falls during the World Wars. From 1950 until the earlier 1970s, we observe a prolonged increase in the ratio, up to a level of 135 metric tons per million of euros in 1973. Since then, the CO_2/GDP ratio has declined persistently up to a level of 76 CO_2 metric tons per million of euros in 2011. The reduction was mainly due to the increased efficiency in the use of energy sources, jointly with the new energy policies implemented in the aftermath of the oil crises of the 1970s, to which it followed a drop of the energy intensity in the manufacturing sector.

The observed historical pattern could reflect the existence of an inverted-U relationship between carbon dioxide emissions and GDP for Italy, along the lines suggested by the EKC literature. Moreover, inspection of the time series suggests the existence of five significant structural breaks in the data more likely explained by the World Wars, and the two oil shocks together with the recent crisis. In what follows we will adopt several distinct, but complementary, approaches to study the relationship between CO_2 emissions and real GDP in Italy.

[9] In the period 1981-1983 Italy experienced economic stagnation. The large industry was facing the repercussions of a second oil shock and the consequences of low profit margins due to the wage-indexing mechanisms, which had been revised in the workers' favour after the first oil shock (see Zamagni (1993) for details).

3 Univariate Properties of CO_2 Emissions and Real GDP in Italy

In the current section we test whether the time series of CO_2 emissions and GDP are driven by some trend, or whether the evolutions over time of these processes exhibit a unit root behavior. We first test for stationarity and then apply a battery of unit root tests studying the time series properties of emissions per capita, and GDP per capita expressed in natural logarithms. An important caveat is in the entity of the WWII shocks and the related statistical treatment. To detect the CO_2 emissions change in the trend of the last decade of the sample, we use the Doornik (2009) algorithm.[10] However, the trivial result obtained, that is three outliers in the error distribution in 1937, 1943 and 1946, suggests that a more deep investigation is needed. Due to the size of the WWII shock to avoid any measurement error problem, instead of dividing the whole sample in two sub-samples, we adopt an alternative approach by smoothing the dimension of the outliers via Hodrick-Prescott filter. This approach allows us to perform a statistically significant analysis without loosing any stylized facts occurring in the sample. Furthermore, to avoid any biases deriving from the quality of the data for the pre-war sample, we also present our results for the sub-sample 1950-2011.

Table 1 presents the results of the applied stationarity and unit root tests for the whole sample, carried out for various lag lengths. To test the stationarity assumption we apply the Kwiatkowski, Phillips, Schmidt, and Shin (1992) (KPSS) test, which has a null hypothesis of stationarity. The KPSS test is often used in conjunction with standard unit root tests to investigate the possibility that a time series is

[10]This is a computer-based approach for the selection of the best statistical model. The logic underlining this strategy is simple: first, it selects a general unrestricted model able to capture all the essential features of the data, that is an autoregressive model augmented by several lagged variables and dummies in order to capture the outlier observations. Then, it selects a value representing the significance level for several diagnostic tests (among them the Chow test for structural change). If the general unrestricted model does not pass these tests, it is reduced of one of the covariates. The procedure is iterated until the model does not pass all the tests.

fractionally integrated. From the results obtained we can reject the null hypothesis of trend and level stationarity for both time series at a 1% level of significance.

We verify the hypothesis that our time series follow a unit-root process by using three different tests. In particular, we analyze our time series data by applying as first the augmented Dickey and Fuller (1979) test (ADF). Since the lag length affects the power properties of the ADF test, we identify the right number of the lags to be included in our model using both the Akaike (1974) Information Criterion (AIC) and the Schwarz (1978)'s Bayesian Information Criterion (BIC). We fail to reject the null hypothesis of unit root for both variables. To achieve an increase in power of the standard ADF test, we also apply its variant test proposed by Elliott, Rothemberg, and Stock (1996), the DF-GLS test, choosing lags according to the Ng and Perron (2001) modified AIC (MAIC), the Schwarz's criterion and sequential t method. With reference to this latter test we fail to reject the null hypothesis of unit root for both series. Finally, according to Phillips and Perron (1988) test results we fail to reject the null hypothesis of unit root for per capita GDP, while for CO_2 emissions we reject the null when a trend term is included in the regression. Reapplication of these tests to the first differences of each time series indicates that both variables are stationary. Thus we can deduce that both time series are integrated of order 1.[11]

We now turn to the sub-sample 1950-2011. Results are reported in Table 2. Again, according to the KPSS test, we can reject the null hypothesis of trend and level stationarity for both time series. The results of the unit root tests instead are mixed and depend on whether a trend is included or not. In particular, while for the DF-GLS test we always fail to reject the null for both time series, for the ADF and the Phillips-Perron tests we fail to reject the null when the trend is included.

As unit-root tests may produce wrong results when time series display structural breaks, especially when a time series exhibits systemic shifts we may fail to reject

[11]Results are available from the authors upon request.

the null of unit root even in the absence of nonstationarity. In order to test the unit root hypothesis, taking into account the possibility of structural breaks in the data, we perform the Zivot and Andrews (1992) test (Zandrews test) and the tests proposed by Clemente, nés, and Reyes (1998). All results are reported in Tables 3 and 4. The Zandrews test allows us to examine for a single structural break in the intercept and in the trend of the time series. The optimal lag length was selected via a t-test. When taking into account the existence of different kinds of structural breaks, we fail to reject the null hypothesis of unit root for both time series in both samples. We notice that the shift in the intercept roughly corresponds to the season of the Italian *economic miracle* around the 1950's, while a structural change in trend is found in 1919 and 2001 for per capita GDP and in 1967 and 1988 for per capita CO_2 emissions.

According to Clemente-Montañés-Reyes unit root tests we proceed considering two alternative events within our time series: the "additive outlier" (CLEMAO) model that captures a sudden change in the series, and the "innovation outlier" (CLEMIO) model that allows a gradual shift in the mean of the series. For convenience, we test for unit root allowing for the existence of one or two structural breaks, in turn. According to the CLEMAO test results we fail to reject the null hypothesis of unit root for both samples and both variables, with the exception of per capita CO_2 in the period 1950-2011, allowing for an additive outlier in 1962. We can conclude that unit roots are present even when instantaneous structural breaks are accounted for. When instead we consider the possibility of innovation outliers, we reject the null for both variables. It is worth noting that when we conduct our analysis on the sub-sample 1950-2011, the CLEMIO test find breaks during the *economic miracle* and at the onset of the recent great recession that struck globally in 2008 and hit Italy harder than expected, after a prolonged period of low growth.

4 Cointegration, Structural Change and Non-Linearities

In this section we study the relationship between carbon dioxide emissions and gross domestic product using different, but complementary, statistical approaches. We start by assuming a "non-stratified" one sided scenario, where CO_2 emissions are created as a by-product of economic activity measured by GDP. Here we assume that both of them have an auto-regressive (AR) structure. This stylized representation permits a better investigation of the peculiarities of the two observed series, which should have same common dynamics. That is the two processes should be cointegrated.

We start by considering the following simple representation of the economy at time t:

$$CO_{2,t} = \phi GDP_t + \epsilon_t \tag{1}$$

where both expressed in log, and ϵ_t is an i.i.d error, indicating all the idiosyncratic elements in the specification of the relationship and ϕ represents the parameter capturing any effect that GDP may have on CO_2 emissions. This representation can be re-written in the following error correction form:

$$\epsilon_t = CO_{2,t} - \phi GDP_t \tag{2}$$

where $[1, -\phi]$ is the cointegrating vector and the linear combination of the two variable assumed to be an $I(0)$-process. In particular, we expect to find some ϕ which is positive so to have a theory-consistent dynamics. The presence of one cointegrating relation may be deduced by the simple graph analysis conducted in Section 2. The graphical analysis clearly shows that the long-run relation between carbon dioxide emissions and gross domestic product in Italy has been changing over time, as result of continuous technology innovation and higher energy efficiency.

Following the Juselius (2006) empirical approach, we study equation (2) estimating a Cointegrated VAR (CVAR or "restricted VAR") model. In particular, after having performed some linearity tests on both variables, we focus on testing if any transition between different regimes (i.e. low emissions, high emissions) are observed. If this latter is the case, we apply a Multiple-Regime Smooth Transition Autoregressive (MR-STAR) model for a univariate scenario for our estimation. The same analysis is also considered in a multivariate context, but the switching regime is assumed to be unobserved, and this is done by estimating a simple Markov-Switching VAR (MS-VAR).The statistical methodologies adopted to investigate the relationship between carbon dioxide emissions and GDP are described in Appendix A. In what follows we summarize the results of our statistical analysis. Both variables under analysis are subject to logarithmic transformation in the CVAR analysis, while for the nonlinear scenarios growth rates are used. The structural break in 1975 observed in the graphical analysis (see Figures 1-4) has been modeled by a broken linear trend in the CVAR starting from this year.

4.1 Linear Scenario: CVAR

In this section we report the cointegration analysis results. We adopt the Juselius (2006) approach to macroeconomic modelling for its fully empirically-based nature. The main findings can be summarized as follows. First, the analysis of the roots of the companion matrix suggests the presence of one unit root in the bivariate process, as shown in Table 5. Second, the Johansen's Trace test is performed and this rejects the hypothesis of $r = 0$, that is no cointegration is observed (see Table 6). The distribution of the Rank Test is approximated by simulating 2500 random processes with length $T = 400$, and restricted linear trend with one break in 1975. Given the above results we select $r = 1$ and introduce a linear trend in the cointegrating relation allowing for a break in 1975, to account for the self-evident change in the levels of emissions. The estimated cointegrating relation is shown in Figure 5.

In Table 7 we report the estimation results of the restricted VAR model with one cointegrating relation and normalized eigenvector β. It shows the required signs in both components of the long-run matrix (this happens independently on the normalization which we settle for the emission variable). The cointegrating vector seems very interesting for its loading sizes [1.000 -2.169]'. This also holds for the resulting eigenvector. The resulting long-run matrix has also the expected signs where a 1% increase in GDP is associated with a 0.062 marginal increase in the emissions growth rate. The residual analysis confirms the normality of the residuals, the presence of an ARCH effect and some skewness and kurtosis problems.

The same Table 7 reports the results of four diagnostic tests discussed in (Juselius, 2006, CH 10-11). The first one is a test on the null hypothesis of redundancy of the variable from the original system of equations: if the model without the variable assumed to be redundant performs better, the investigator will be allowed to reduce the dimension of the VAR. In this case, when the VAR is augmented to include the global trend and the 1975-trend, both variables are not significant. The second test is a classical ADF test on each single equation of the system. We observe that for both variables the null of stationarity can be rejected consistently with the findings of the previous section. This result suggests the need to estimate a restricted model able to capture a latent (stationary) trend. We test for omitted variables and for no correlation of the independent variables with the error term (weak endogeneity). The third third test shows that none of the two variables is significantly weakly exogenous. This finding is consistent with the result of the exclusion test according to which we need both equations in the system to capture the long-run dynamics. Finally, the fourth test suggests that the null of endogeneity is rejected for both of the variables. This means that none of the variables is permanently affected whether a shock is produced on the system and it is not possible to detect which variable "drives" the other.

These diagnostic checks on the estimated CVAR model and in particular the results of the last two tests seem to suggest opposite conclusions. The bivariate nature of system and the by-product nature of the CO_2 with respect to GDP explain in some way the difficulty to distinguish between "pulling and pushing forces". This leads us to stop the investigation via CVAR model in favor of different approaches.

4.2 Nonlinear Scenario: Linearity Tests

Before moving to the nonlinear models, in this section we perform some tests for linearity on our studied variables. Table 8 provides the results of four different tests for linearity. In the Tsay (1989) test the null of linearity is rejected if a delay of 1 year is used in the output variable (2 in emissions), while the Luukkonen, Saikkonen, and Teräsvirta (1988) test requires at least $d = 2$ in order to have evidence of nonlinearity. In all cases one could not reject the null of linearity because all p-values are high. We applied the Tsay rule for detecting the right parameter d by searching the one for which the p-value is minimum. For $d = 2$ the p-value is relatively lower than in the other cases, thus we selected SETAR(4; 2) and SETAR(1;2) models. The Hansen (1996) test for the no-threshold effect confirms the previous findings for the output series, while for the emissions it seems to be quite near to linearity (the p-value single LM-statistics is always higher than 5%). However, the SETAR estimates shown in Table 8 seem to leave no doubt to the fact that there is some change in the sample mean.

4.3 Nonlinear Scenario: MR-STAR

The estimated MR-STAR models for our GDP are defined below (where the values in brackets are the standard errors):

$$
\begin{aligned}
GDP_t = & \underset{[0.0100]}{-0.0020} + \underset{[0.1065]}{0.1917} GDP_{t-1} \underset{[0.2154]}{-0.3259}\, GDP_{t-2} \underset{[0.1835]}{0.6274} GDP_{t-3} \underset{[0.1853]}{-0.1168}\, GDP_{t-4} \\
& + (\underset{[0.0133]}{0.0093} \underset{[0.2045]}{-0.3747}\, GDP_{t-1} \underset{[0.4035]}{1.0940} GDP_{t-2} \underset{[0.2411]}{-0.7707}\, GDP_{t-3} + \underset{[0.2289]}{0.1854} GDP_{t-4}) \\
& \times G(GDP_{t-3}; \underset{[49.817]}{20.000}; \underset{[0.1864]}{-0.0378}) \\
& - (\underset{[0.0274]}{0.0860} \underset{[0.3079]}{-0.7310}\, GDP_{t-1} + \underset{[0.4885]}{0.2004} GDP_{t-2} + \underset{[0.2046]}{0.5471} GDP_{t-3} + \underset{[0.1852]}{0.1238} GDP_{t-4}) \\
& \times G(GDP_{t-3}; \underset{[20.8127]}{20.003}; \underset{[0.0628]}{1.2670})
\end{aligned}
\tag{3}
$$

$$
\begin{aligned}
CO_{2,t} = & \underset{[0.0342]}{0.0941} + \underset{[0.1463]}{0.1952} CO_{2,t-1} \\
& + (\underset{[0.0381]}{-0.0692} - \underset{[0.1906]}{0.2630} CO_{2,t-1}) \times G(CO_{2,t-3}; \underset{[49.9697]}{20.002}; \underset{[0.1382]}{-0.3165}) \\
& + (\underset{[0.0413]}{0.0862} - \underset{[0.2496]}{0.6477} CO_{2,t-1}) \times G(CO_{2,t-3}; \underset{[51.9176]}{20.003}; \underset{[0.01533]}{1.0566})
\end{aligned}
\tag{4}
$$

In this analysis we include the emission intensity, defined as the natural log of the ratio CO2/GDP, labeled EI. The estimated MR-STAR model for the emission intensity is defined as

$$
\begin{aligned}
EI_t = & \underset{[0.0237]}{-0.0162} + \underset{[0.1463]}{0.1348} EI_{t-1} \\
& + (\underset{[0.0298]}{0.0613} + \underset{[0.1825]}{0.0558} EI_{t-1}) \times G(EI_{t-3}; \underset{[40.8913]}{20.001}; \underset{[0.1382]}{-0.1473}) \\
& + (\underset{[0.0383]}{-0.0363} \underset{[0.1299]}{-0.5932}\, EI_{t-1}) \times G(EI_{t-3}; \underset{[73.3032]}{20.002}; \underset{[0.1894]}{1.0770}),
\end{aligned}
\tag{5}
$$

where in brackets we report the standard errors. Figure 6 shows the two estimated transition functions for the three variables. In all sub-plot, the first panel describes the G function versus the transition variable s_t. This enables us to visualize the path of the transition of the variable from state 0 (low emissions) to state 1 (high emissions), measured by the steep parameter γ. The second panel shows the same function versus time, allowing us to visualize the duration of each regime change expressed in number of years, and when such change has occurred. The transitions are clearly identified by the two structural shocks happened in 1881-1891 decade, and during the second half of the Seventies[12]. The first transition seems to be more persistent than the second one, in particular for the emissions, where the new regime is reached only at the end of WWI. It is worth noticing that the WWII is not considered as the beginning of a new regime. This result is consistent with what observed in the Italian history.

4.4 Nonlinear Scenario: MS-VAR

In this subsection we move to a multivariate scenario by allowing for an unobserved change in the regime of the system from state 0 (high GDP growth, high CO_2 growth) to state 1 (low GDP growth, low CO_2 growth).

The coefficients of the selected VAR(1) reported in Table 9 show a preponderance of the state 0, especially for CO_2 emissions. In particular, there is an evident asymmetry of the duration with respect the two states (28 years vs. 19 years on average). Figure 7 reports the estimated conditional means and standard deviations and the estimated state of the VAR process for each equations. With respect to the MR-STAR model, the MS-VAR model is more sensitive to the non-structural shocks, as shown by the change in regime after the post WWI and WWII periods. It is important to notice that the post-1975 reversed trend in CO_2 emissions is now more problematic to justify. State 0 appears to be more persistent since the mid '50s, with just a break occurring during the last years of the Seventies. As a matter of fact, it seems that the state of high growth/high pollution is permanent until the Great Recession in 2008.

[12]On the contrasting interpretations of the economic events of 1880s, see Fenoaltea (2011) who remarks that two major external developments affected the Italian economy in that decade: (i) a strong increase in the supply of foreign capital, along with (ii) a sharp fall in the price of imported grain.

5 Testing the EKC for Italy

In this section we test for the existence of a systematic relationship between pollution and economic growth, commonly referred to as Environmental Kuznets Curve (EKC). According to the EKC hypothesis, environmental degradation tends to increase as the economy develops, but begins to decline at higher levels of income. The existence of a systematic a bell-shaped relationship between pollutant and income is still an open issue and the results of the empirical literature are controversial.[13] Aware of the limits of this approach we test the EKC hypothesis adopting two strategies. First we estimate a standard polynomial relationship between per capita carbon dioxide emissions and per capita GDP for Italy. Then we replace the polynomial specification with a flexible non-linear model of per capita GDP. We model the polynomial relationship between carbon dioxide emissions and gross domestic product, as follows:

$$CO_{2,t} = \gamma_0 + \gamma_1 GDP_t + \gamma_2 GDP_t^2 + \varepsilon_t, \qquad (6)$$

where ε_t denotes the error term and, as before, all variables are expressed in per capita terms and converted in natural logarithms. The turning point income, where pollutant emissions reach the peak is given by $\tau = e^{-\gamma_1/2\gamma_2}$. The parameters γ_1 and γ_2 are long-term elasticities of carbon dioxide per capita emissions with respect to per capita real GDP, and squared per capita real GDP, respectively. An inverted-U relationship between GDP and CO_2 requires that $\gamma_1 > 0$ and $\gamma_2 < 0$.

We estimate the EKC model (6) for the whole sample, 1861-2011, and for the subset 1950-2011, using GLS in order to consider possible serial correlation. In the presence of autocorrelated disturbances the standard errors estimated by OLS are likely to be too small. Results are reported in Table 10. The estimated coefficients of the linear term and of the quadratic term are highly significant, and exhibit the theoretically

[13]For reviews of the EKC literature see e.g. Stern (1998a,b); Millimet, List, and Stengos (2003); de Bruyn and Heintz (1999); Dinda (2004) *inter alia*.

expected sign.

Test results show the presence of serially correlated residuals and of heteroskedasticity. According to the results of the Ramsey's RESET test, there is functional form misspecification. In general, we notice that the statistical quality of the estimation, in terms of measures of goodness of fit, is much better for the second sub-period 1950-2011 than for the whole sample. In the quadratic specification the turning points for CO_2 emissions are estimated to occur at a per capita real GDP value of $34,720$ and $74,078$ Euros, respectively. It should be noticed that in 2011 the per capita GDP of Italy was about $23,514$ Euros. With this regard, our estimates about the chances for Italy to curb carbon dioxide emissions are very pessimistic. Figure 8 plots the fitted values of the quadratic model over the period 1861-2011, while Figure 9 plots the residuals. We now turn to the results of the flexible non-linear model. In particular we consider a restricted cubic spline model, where per capita carbon dioxide emissions are modeled as a restricted cubic spline function of per capita GDP for the whole sample. Restricted cubic splines are such that: (i) below the first and above the last knot the function should be linear; (ii) within each interval the function should be cubic; (iii) at each knot the function should be continuous and smooth with continuous first and second derivatives. Figure 10 plots the fitted values of the cubic spline model together with the observed data. To check the adequateness of the fitted spline we also compare the residuals of the spline model with those obtained with the quadratic model. See Figure 11. Clearly, the second specification appears to be more adequate in representing the behaviour of carbon dioxide emissions with respect to GDP, confirming that the more flexible structure allowed by the cubic piecewise model outperforms the rigid structure imposed by the standard quadratic model.

6 Conclusions

Environmental awareness has become a central issue in the policy debate. Given the heavy reliance of Italy on fossil fuels, the reduction of carbon dioxide emissions for the accomplishment of the Europe 2020 strategy remains a serious environmental and policy challenge.

In this paper we have analyzed the relationship between income growth and carbon dioxide emissions for Italy, in a historical perspective. Using several different statistical techniques, our results suggest that the CO_2 emission trajectory is closely related to the income time path, and that the behavior of emission intensity and of the main two series are highly nonlinear. There seems to be a common trend between real GDP and CO_2, which however changes direction in the middle of the Seventies, suggesting a possible slowdown in the emission intensity, probably due to the energy efficiency policies implemented in the aftermath of the oil crises of the 1970s. Consistently, according to the MR-STAR analysis, a structural shock may have occurred in the same period, marking a slowdown in the growth rate of carbon dioxide emissions. However, the MS-VAR suggests that the state of high growth/high pollution seems to be permanent until the recent recession. In addition, the EKC analysis shows the existence of a bell-shaped relationship between income and the pollutant, but according to the estimates, the predicted turning point turns out to be pessimistically high.

Overall, our results do not seem to unambiguously show a structural slowdown of carbon dioxide emissions in recent years, that is why we argue that meeting the climate change and energy sustainability goals of the Europe 2020 strategy represents a very challenging task calling for a radical policy shift.

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A Statistical Models

A.1 CVAR

For what concerns the cointegration analysis of the relationship between Italian output and emissions, we use a VAR(p) to model relations (1) or (2):

$$\boldsymbol{y_t} = \boldsymbol{\Pi_1 y_{t-1}} + \cdots + \boldsymbol{\Pi_p y_{t-p}} + \boldsymbol{\Phi D_t} + \boldsymbol{\epsilon_t} \quad t = 1, \ldots, T, \;\; \boldsymbol{\epsilon_t} \sim \mathcal{N}_p(\boldsymbol{0}, \boldsymbol{\Omega}) \tag{7}$$

The Error Correction Model of model (7) is[14]

$$\boldsymbol{\Delta y_t} = \boldsymbol{\Gamma_1^{(1)} \Delta y_{t-1}} + \boldsymbol{\Gamma_2^{(1)} \Delta y_{t-2}} + \cdots + \boldsymbol{\Gamma_{p-1}^{(1)} \Delta y_{t-p-1}} + \boldsymbol{\Pi y_{t-1}} + \boldsymbol{\Phi D_t} + \boldsymbol{\epsilon_t} \tag{8}$$

where: $\boldsymbol{\Gamma_1^{(1)}} = -(\boldsymbol{\Pi_2} + \boldsymbol{\Pi_3} + ... + \boldsymbol{\Pi_p})$, $\boldsymbol{\Gamma_2^{(1)}} = -(\boldsymbol{\Pi_3} + \cdots + \boldsymbol{\Pi_p})$ and $\boldsymbol{\Pi} = -(\boldsymbol{I} - \boldsymbol{\Pi_1} - \boldsymbol{\Pi_2} - \cdots - \boldsymbol{\Pi_p})$ are the short-run matrices and the long-run matrix, respectively where the integer (1) indicates the lag placement of ECM. Notice that $\boldsymbol{\Pi} = \boldsymbol{\alpha\beta'}$ is the reduced rank long-run matrix, with $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are $p \times r$ matrices, $r \leq p$, $\boldsymbol{\Phi D_t} = \boldsymbol{\mu_0} + \boldsymbol{\mu_1} t$ are the unrestricted components (i.e. allowed to enter into the cointegrating relation) of deterministic trend and $\boldsymbol{y_t} = [CO_{2,t}, GDP_t]'$. Equation (7) is the CVAR model in Error Correction Form under I(1) hypothesis[15].

A.2 MR-STAR

To model for the change in the Italian economic structure during the 150 years of our sample we use the MR-STAR model. We consider the general additive non-linear model as follows:

$$y_t = \boldsymbol{\phi' z_t} + \boldsymbol{\theta' z_t} \sum_{m=1}^{M} G(\boldsymbol{\gamma}, \boldsymbol{c}, s_t) + \epsilon_t \tag{9}$$

where y_t is the dependent variable, $\boldsymbol{z_t} = (1, y_1, \ldots, y_{t-p})'$, $\boldsymbol{\phi} = (\phi_0, \phi_1, \ldots, \phi_p)'$, $\boldsymbol{\theta} = (\theta_0, \theta_1, \ldots, \theta_p)'$ are parameter vectors, and $\epsilon_t \sim i.i.d.(0, \sigma^2)$. The transition function $G(\boldsymbol{\gamma}, \boldsymbol{c}, s_t)$ is a continuous function in the transition variable s_t, where the parameter vector $\boldsymbol{\gamma} = (\gamma_1, \ldots, \gamma_m, \ldots \gamma_M)$ controls the velocity of the M transitions with $\boldsymbol{c} = (c_1, \ldots, c_m, \ldots c_M)$ assumed as a vector of transition parameters. For what follows we suppose that the transition variable coincides with a lagged value of the endogenous variable y_t with lag denoted by delay $d > 0$.
One of the main used functions for $G(\cdot)$ is the (first order) logistic function:

$$G(\boldsymbol{\gamma}, \boldsymbol{c}, s_t) = \left(1 + exp\left\{-\gamma_M \prod_{k=1}^{K} (s_t - c_m)\right\}\right)^{-1}, \;\; \gamma > 0, \tag{10}$$

where $\gamma_m > 0$ and $c_1 < \cdots < c_m < \cdots < c_M$ are identifying restrictions. Equations (10) and (9) define the first-order (Multiple-Regime) Logistic STAR (MR-LSTAR1) model. The most common choices is to set alternatively $K = 1$, whether the parameters $\boldsymbol{\phi} + \boldsymbol{\theta} G(\gamma, \boldsymbol{c}, s_t)$ change monotonically as a function of s_t from $\boldsymbol{\phi}$ to

[14] See (Juselius, 2006, Section 4.2.2).

[15] For further details, see Johansen (1991)

$\boldsymbol{\phi} + \boldsymbol{\theta}$, and $K = 2$, in case the parameters $\boldsymbol{\phi} + \boldsymbol{\theta} G(\gamma, \boldsymbol{c}, s_t)$ change symmetrically around the mid-point $(c_1 + c_2)/2$, where the logistic function attains its minimum, $min_G G(\cdot) \in [0, 1/2]$, that is:

$$min_G G(\cdot) = \begin{cases} 0 & if \;\; \gamma \to \infty \\ 1/2 & if \;\; c_1 = c_2 \;\; and \;\; \gamma < \infty \end{cases}$$

If $\gamma_m = 0$ the transition function will be $G(\gamma_m, \boldsymbol{c}, s_t) \equiv 1/2$, so that model (9) will nest a linear model. When $\gamma_m \to \infty$ the model (9) nests a SETAR model (Tong (1983)):

$$y_t = \sum_{j=1}^{r+1} (\boldsymbol{\phi}_j' \boldsymbol{y_t}) I\big(y_{t-d} \leq c_j\big) + \sum_{j=1}^{r+1} (\boldsymbol{\phi}_j' \boldsymbol{y_t}) I\big(y_{t-d} > c_j\big) + \epsilon_{jt} \tag{11}$$

where $\boldsymbol{\phi}, \boldsymbol{y_t}$ are defined as before, s_t is a continuous switching random variable, $c_0, c_1, \ldots, c_{r+1}$ are threshold parameters, $c_0 = -\infty$, $c_{r+1} = +\infty$, $\epsilon_{jt} \sim i.i.d.(0, \sigma_j^2)$, $j = 1, \ldots, r$. The multiple regime hypothesis is investigated via LM test, and the most likely number of regimes can be obtained by iteration.

A.3 MS-VAR

The MR-STAR model assumes that transition between regimes is observed. This assumption can be removed by using a Markov Chain structure in the transition between the same (multiple) regimes. To this scope we use a Markov-Switching VAR model [16], having the p-th order autoregression for the K-dimensional time series vector $y_t = (y_{1t}, \ldots, y_{Kt})$, $t = 1, \ldots, T$,

$$\boldsymbol{y}_t = \boldsymbol{\mu}_0 + \boldsymbol{\Pi}_1(s_t) y_{t-1} + \cdots + \boldsymbol{\Pi}_p(s_t) y_{t-p} + \boldsymbol{u}_t, \tag{12}$$

where $\boldsymbol{\Pi}$ is defined as in the subsection A.1 with no interest for the $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ partition, $\boldsymbol{u}_t \sim IID(\boldsymbol{0}, \boldsymbol{\Sigma})$ and $y_0, \ldots, y_{1-p}$ are fixed, $s_t \in (1, \ldots, M)$ is the unobservable regime variable representing the probability of being in a different state of the world, which is governed by a discrete time, a discrete state, and a irreducible ergodic M state Markov process with the transition probabilities matrix defines as:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1M} \\ p_{21} & p_{22} & \cdots & p_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ p_{M1} & p_{M2} & \cdots & p_{MM} \end{bmatrix} \tag{13}$$

where p_{ij} the probability of switching from state i to state j, that is

$$p_{ij} = Pr(s_{t+1} = j | s_t = i), \quad \sum_{j=1}^{M} p_{ij} = 1 \;\; \forall i, j \in \{1, \ldots, M\} \tag{14}$$

[16] See also Krozlig (1997).

Denoting $A(L) = \mathbf{I}_K - \mathbf{\Pi}_1 L - \ldots, -\mathbf{\Pi}_p L^p$ as the $(K \times K)$ dimensional lag polynomial, we assume that there are no roots on or inside the unit circle $|\mathbf{\Pi}(z)| \neq 0$ for $|z| \leq 1$ where L is the lag operator, so that $y_{t-j} = L^j y_t$. If a normal distribution of the error is assumed, $u_t \sim NID(0, \Sigma(s_t))$, equation (12) is known as the intercept form of a stable Markov Switching Gaussian VAR(p) model.

B Tables and Graphs

Table 1: Unit Root and Stationarity Tests for Per Capita GDP and CO_2 Emissions, 1861-2011

	Per Capita GDP		*Per Capita CO_2*	
	no trend	with trend	no trend	with trend
KPSS	14***	3.21***	13.9***	0.76***
ADF	0.946(1)	−1.677(1)	−1.896(2)	−2.493(2)
	1.385(0)	−1.634(0)	−1.896(2)	−2.493(2)
	1.145(3)	−1.175(3)	1.653(1)	−0.986(1)
DF-GLS	−0.523(12)	−1.175(3)	1.301(2)	−1.198(2)
	−0.523(12)	−1.952(12)	1.301(2)	−1.198(2)
Phillips-Perron	0.544	−1.725	−2.080	−3.349**

NOTES: Variables in natural logs. Lags reported in parentheses. A single asterisk, *, indicates significance at 10% level, a double asterisk, **, at 5% level and a triple asterisk, ***, at 1%. For the ADF the first row reports the statistic with the lag selected using the AIC, the second using the BIC. For the DF-GLS lags selected using the Schwarz's information criterion, the Ng-Perron modified Akaike information criterion (MAIC) and the Ng-Perron sequential t method, respectively.

Table 2: Unit Root and Stationarity Tests for Per Capita GDP and CO_2Emissions, 1950-2011

	Per Capita GDP		Per Capita CO_2	
	no trend	with trend	no trend	with trend
KPSS	5.81^{***}	1.44^{***}	4.65^{***}	1.37^{***}
ADF	$-7.541^{***}(0)$	$0.127(0)$	$-3.950^{***}(2)$	$-1.936(0)$
	$-7.541^{***}(0)$	$0.127(0)$	$-7.498^{***}(0)$	$-1.936(0)$
DF-GLS	$-1.005(6)$	$0.249(0)$	$-0.115(2)$	$-0.700(2)$
	$-1.005(6)$	$-1.033(6)$	$-0.115(2)$	$-0.700(2)$
	$-1.556(10)$	$-1.424(10)$	$-0.881(6)$	$-1.334(6)$
Phillips-Perron	-6.886^{***}	0.220	-6.052^{***}	-1.818

Notes: Variables in natural logs. Lags reported in parentheses. A single asterisk, *, indicates significance at 10% level, a double asterisk, **, at 5% level and a triple asterisk, ***, at 1%. For the ADF the first row reports the statistic with the lag selected using the AIC, the second using the BIC. For the DF-GLS lags selected using the Schwarz's information criterion, the Ng-Perron modified Akaike information criterion (MAIC) and the Ng-Perron sequential t method, respectively.

Table 3: Unit Root Tests with Structural Breaks for Per Capita GDP and CO_2 Emissions, 1861-2011

	Per Capita GDP		*Per Capita CO_2*	
	test statistics	Year	test statistics	Year
Zandrews (break in intercept)	$-4.538(3)$	1947	$-3.123(2)$	1959
Zandrews (break in trend)	$-2.287(3)$	1919	$-2.809(2)$	1988
CLEMAO1	-2.791	1964	-1.888	1947
CLEMAO2	-1.891	1954, 1975	-3.561	1891, 1957
CLEMIO1	-6.705^{**}	1945	-4.550^{**}	1944
CLEMIO2	-5.490^{**}	1898, 1945	-5.490^{**}	1941, 1944

NOTES: Variables in natural logs. Lags reported in parentheses. For the Zandrews statistics lags selected via t test. A single asterisk, *, indicates significance at 10% level, a double asterisk, **, at 5% level and a triple asterisk, ***, at 1%.

Table 4: Unit Root Tests with Structural Breaks for Per Capita GDP and CO_2 Emissions, 1950-2011

	Per Capita GDP		*Per Capita CO_2*	
	test statistics	Year	test statistics	Year
Zandrews (break in intercept)	0.997(0)	1959	−3.966(1)	1960
Zandrews (break in trend)	−1.087(0)	2001	−3.517(1)	1967
CLEMAO1	−2.675	1973	-3.603^{*}	1962
CLEMAO2	−3.223	1969, 1989	−4.031	1963, 1973
CLEMIO1	-7.342^{**}	1957	-8.764^{**}	1958
CLEMIO2	-7.362^{**}	1957, 2008	-8743^{**}	1958, 2007

NOTES: Variables in natural logs. Lags reported in parentheses. For the Zandrews statistics lags selected via t test. A single asterisk, *, indicates significance at 10% level, a double asterisk, **, at 5% level and a triple asterisk, ***, at 1%.

Table 5: The Roots of Companion Matrix

	Real	Imaginary	Modulus	Argument
Root 1	1.000	0.000	1.000	0.000
Root 2	0.975	0.000	0.975	0.000
Root 3	0.278	0.608	0.668	1.143
Root 4	0.278	−0.608	0.668	−1.143
Root 5	−0.564	−0.341	0.659	−2.599
Root 6	−0.564	0.341	0.659	2.599
Root 7	−0.312	0.518	0.604	2.113
Root 8	−0.312	−0.518	0.604	−2.113
Root 9	0.514	−0.229	0.562	−0.420
Root 10	0.514	0.229	0.562	0.420

NOTE: software used: CATS for RATS

Table 6: The Simulated Trace Test Distribution

		Simulated Trace Test Distribution		
p-r	r	Eig.Value	Trace	P-Value
2	0	0.273	55.990	0.000
1	1	0.063	9.470	0.353

		Quantiles of the Simulated Distribution							
p-r	r	Mean	S.E.	50%	75%	80%	85%	90%	95%
2	0	20.551	5.786	19.939	23.971	25.253	26.450	27.973	31.019
1	1	8.565	3.826	7.875	10.474	11.324	12.338	13.654	15.662

NOTE: software used: CATS for RATS

Table 7: The Estimated CVAR

		Normalized β'			
	CO2	GDP	T(1975)	TREND	
	1.000 [NA]	−2.169 [−2.607]	−0.078 [−2.619]	−0.044 [3.431]	
		α			
DCO2		−0.029 [−3.060]			
DGDP		0.010 [3.856]			
		Π			
	CO2	GDP	T(1975)	TREND	
DCO2	−0.029 [−3.060]	0.062 [3.060]	0.002 [3.060]	0.001 [−3.060]	
DGDP	0.010 [3.856]	−0.022 [−3.856]	−0.001 [−3.856]	0.000 [3.856]	
		Log-likelihood = 844.704			
Tests for autocorrelation[(a)]		Normality Test[(b)]	ARCH effects[(a)]		
Ljung-Box(36): $\chi^2(126)$	164.403 [0.012]	56.094 [0.000]			
LM(1): $\chi^2(4)$	1.237 [0.872]		LM(1): $\chi^2(9)$	58.879 [0.000]	
LM(2): $\chi^2(4)$	6.583 [0.160]		LM(2): $\chi^2(18)$	66.738 [0.000]	
		Descriptive Statistics			
	Mean	Std. Dev.	Skewness	Kurtosis	
DCO2	0.000	0.114	-1.145	9.992	
DGDP	0.000	0.032	-0.368	6.386	
	Maximum	Minimum	ARCH(5)	Normality	
DCO2	0.388	-0.628	11.564 [0.041]	59.275 [0.000]	
DGDP	0.142	-0.112	36.418 [0.000]	41.705 [0.000]	
	R^2				
DCO2	0.192				
DGDP	0.246				
		Diagnostic Tests[(c)]			
TEST	STATISTIC	CO2	GDP	T(1975)	TREND
Exclusion	$LR(\nu_1)$	3.811 [0.051]	5.122 [0.024]	4.940 [0.026]	6.680 [0.010]
Stationarity	$LR(\nu_2)$	5.122 [0.024]	3.811 [0.051]		
Weak Exogeneity	$LR(\nu_1)$	7.414 [0.006]	11.525 [0.001]		
Unit vector in α	LR(ν_3)	11.525 [0.001]	7.414 [0.006]		

NOTES: Effective sample: 1866-2011 (146 obs.); No. observations - no. variables: 132; selected no. lags in VAR: 5; (a) Number of degree-of-freedom in parenthesis, p-values in squared brackets; (b) Distributed as $\chi^2(4)$, p-values in squared brackets; (c) All tests are distributed as $\chi^2(\nu_i)$, i=1, ..., 3, $\nu_1 = rm$, m restrictions on each rank r, $\nu_2 = r - n_b$, with r rank restriction and n_b number of known cointegrating vectors, $\nu_3 = p - r$, with p rank restriction and n_b number of known cointegrating vectors; Software used: RATS

Table 8: Linearity Testing and TAR Model Estimates

SERIES	DGDP				DCO2				DCO2			
	d=1	d=2	d=3	d=4	d=1	d=2	d=3	d=4	d=1	d=2	d=3	d=4
Tsay test	$1.23e^{-6}$	0.058	0.456	$1.02e^{-05}$	0.989	**0.003**	0.218	0.630	0.644	0.045	0.068	0.056
LST test	0.191	**0.000**	0.000	0.000	0.172	**0.011**	0.024	0.003	0.1616	0.0072	0.0247	0.0398
	Hansen's test											
Statistic	SupLM	ExpLM	AveLM	No Thr.	SupLM	ExpLM	AveLM	No Thr.	SupLM	ExpLM	AveLM	No Thr.
bootstrap p-val	0.001	0.000	0.001	0.004	0.114	0.072	0.057	0.044	0.082	0.206	0.334	0.1674

TAR estimates

Threshold:	0.0025			0.0737			0.0815		
Regressor	Full Sample	<= Thrsh	>Thrsh	Full Sample	<= Thrsh	>Thrsh	Full Sample	<= Thrsh	>Thrsh
const	0.0080 [0.0036]	0.0080 [0.0115]	−0.0048 [0.0041]	0.0371 [0.0112]	0.0261 [0.0130]	0.1408 [0.0356]	0.0196 [0.0100]	0.0090 [0.0111]	0.1459 [0.0423]
ϕ_{t-1}	0.1714 [0.0837]	−0.1239 [0.2915]	0.3777 [0.0972]	−0.1044 [0.0774]	−0.0902 [0.1189]	−0.5605 [0.1760]	−0.1733 [0.0758]	−0.2242 [0.1142]	−0.6519 [0.1934]
ϕ_{t-2}	0.1067 [0.0830]	[0.2313]	0.1771 [0.0664]						
ϕ_{t-3}	0.2147 [0.0842]	−0.0028 [0.2705]	0.1902 [0.0655]						
ϕ_{t-4}	0.0119 [0.0851]	−0.4848 [0.2189]	0.2142 [0.0689]						

NOTES: No. of lags selected according to AIC and BIC for lags $\{1,\ldots,12\}$; Software used: RATS

Table 9: MS-VAR: Estimates

Feature	Value			
Final Log-likelihood:	464.5412			
No. of estimated parameters:	18			
No. of Observations:	150			
No. of VAR lags (according to BIC):	1			
Expected Duration for Regime 0	28.11			
Expected Duration for Regime 1	18.76			
Parameter (SE in brakets)	Eq. 1		Eq. 2	
	S0	S1	S0	S1
Const	0.02 [0.01]	0.01 [0.03]	0.01 [0.00]	0.00 [0.01]
DCO2	1.08 [0.28]	−0.53 [0.00]	0.74 [0.07]	−0.11 [0.15]
DGDP	−0.01 [0.09]	0.02 [0.14]	0.00 [0.03]	0.01 [0.04]
Transition Matrix (p-value in brakets)				
Final State Probability	$P_{i\|1}$		$P_{i\|2}$	
$P_{1\|j}$	0.96 [<0.001]		0.05 [<0.001]	
$P_{2\|j}$	0.04 [<0.001]		0.95 [<0.001]	

NOTE: Software used: MatLab 2009b

Table 10: Environmental Kuznets Curve for Italian CO_2 Emissions, 1861-1959

	1861-2011		1950-2011	
	Linear	Quadratic	Linear	Quadratic
constant	2.7074^{***} (0.3449)	1.7114^{***} (0.3957)	3.4041^{***} (0.4420)	2.1001^{***} (0.5285)
GDP_t	1.6411^{***} (0.1647)	3.3920^{***} (0.5224)	1.3699^{***} (0.1108)	2.7985^{***} (0.4669)
GDP_t^2		-0.4781^{***} (0.1378)		-0.3250^{***} (0.1012)
$DW1975$				
ρ	0.9531	0.8988	0.9957	0.9875
turning point τ	NA	$34,720$	NA	$74,078$
obs.	151	151	62	62
F statistic	24.32^{***}	57.77^{***}	237.64^{***}	289.96^{***}
Adj. R^2	0.13	0.43	0.89	0.90
AIC	-175.121	-162.0127	-236.5118	-243.6991
BIC	-169.0865	-152.9608	-232.2576	-237.3177
log-likelihood	89.5605	84.0064	120.2559	124.8496
RESET	8.03^{***}	4.46^{***}	5.25^{***}	5.17^{***}
BP	15.85^{***}	27.57^{***}	32.74^{***}	27.56^{***}
BG(1)	5.330^{**}	6.564^{***}	6.977^{**}	6.849^{***}
ARCH(1)	5.538^{**}	4.331^{**}	3.720^{**}	4.941^{**}
DW	2.29	2.34	2.35	2.35

NOTES: Variables in natural logs. The regressions are estimated by GLS based on the Prais-Winsten transformation. Standard errors are in parentheses. A single asterisk, *, indicates significance at 10% level, a double asterisk, **, at 5% level and a triple asterisk, ***, at 1%; ρ is the estimated autocorrelation parameter; obs. denotes the number of observations; NA: not applicable because the coefficients are not significant in the quadratic specification and the relationship appears to be increasing. AIC is the Akaike information criterion value; BIC is Schwarz's Bayesian information criterion; the RESET is the Ramsey specification test for omitted variables; BP is the Breusch-Pagan test for heteroskedasticity; BG is the Breusch-Godfrey LM test for the presence of first order autocorrelation; ARCH(1) is the Engle's LM test for autoregressive conditional heteroskedasticity of order 1; D-W is the Durbin-Watson d statistic to test for first-order serial correlation.

Figure 1: Per Capita GDP in Italy, 1861-2003 *(Thousands of 2005 Euros Per Capita)*

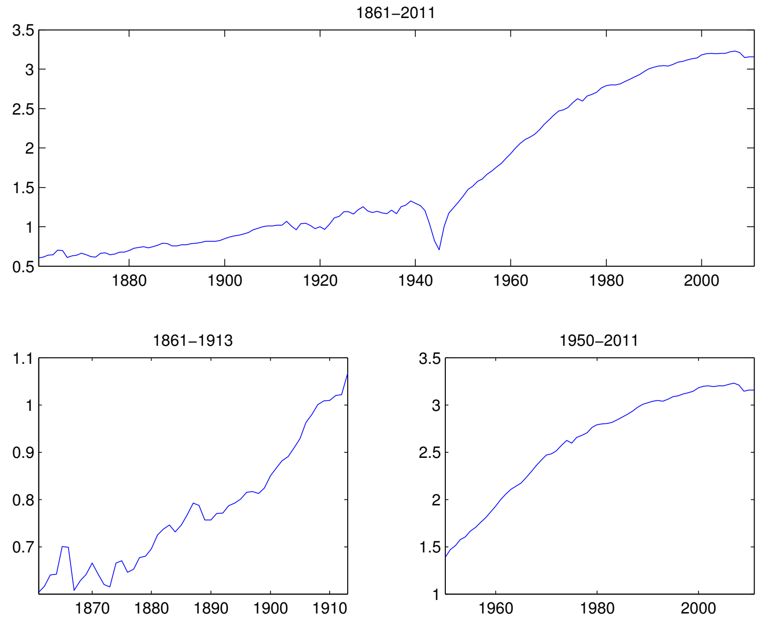


Figure 2: Per Capita CO_2 Emissions in Italy, 1861-2003 (Kilos Per Capita)

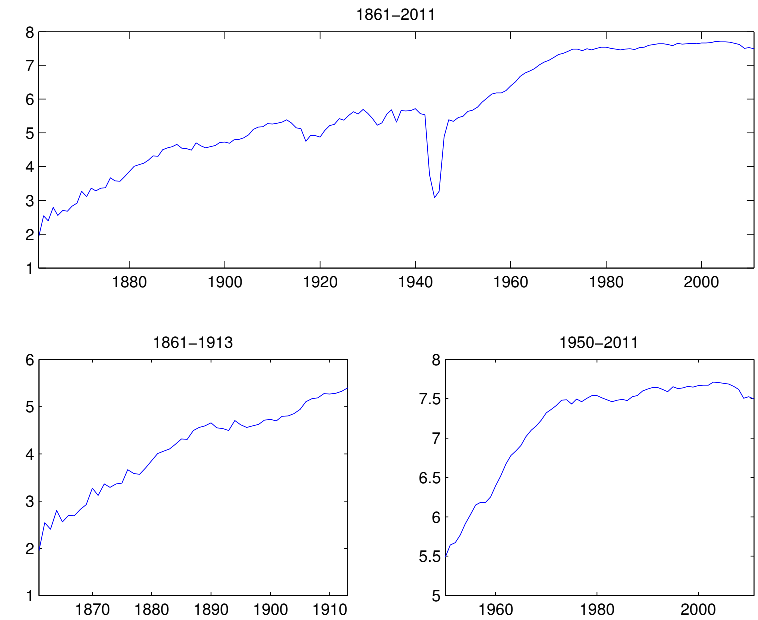


Figure 3: Per Capita CO_2 Emissions and Per Capita GDP in Italy, 1861-2003

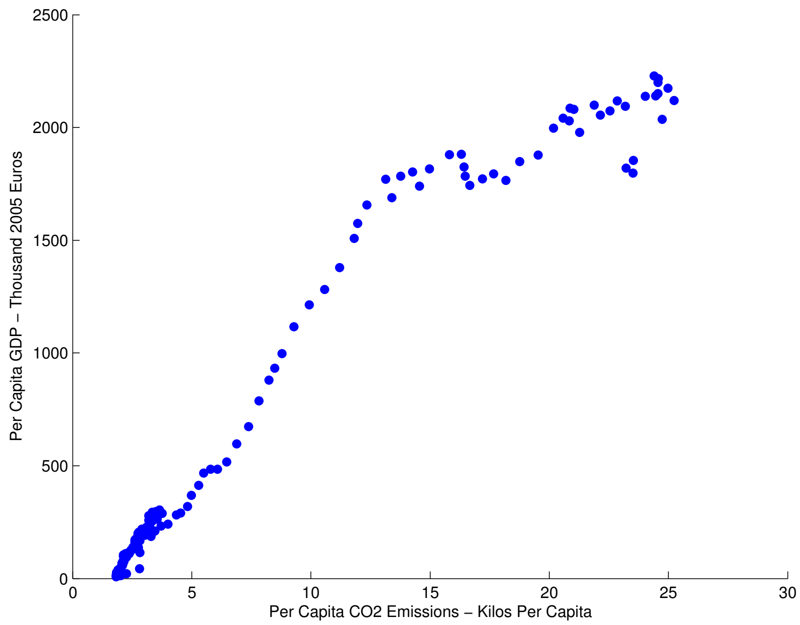


Figure 4: CO_2/GDP Ratio in Italy, 1861-2003 *(Metric Tons per Million of Euros)*

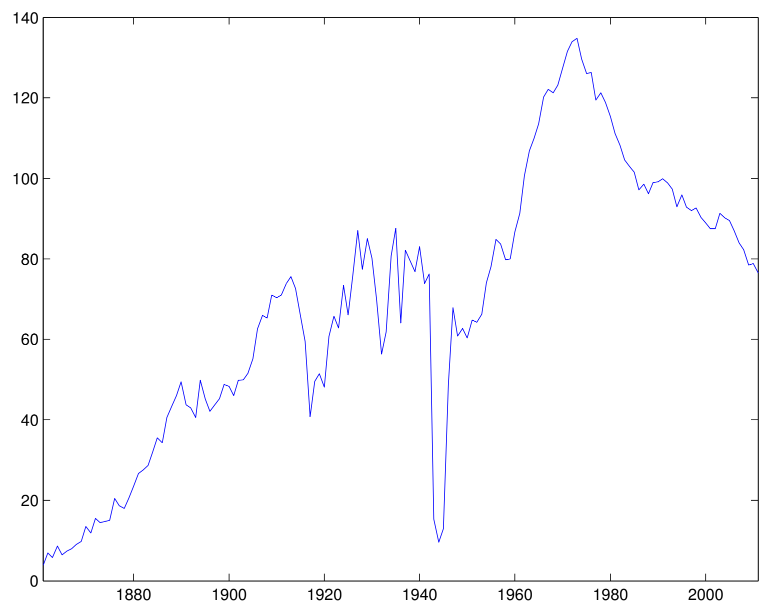


Figure 5: The Estimated Cointegrating Vector

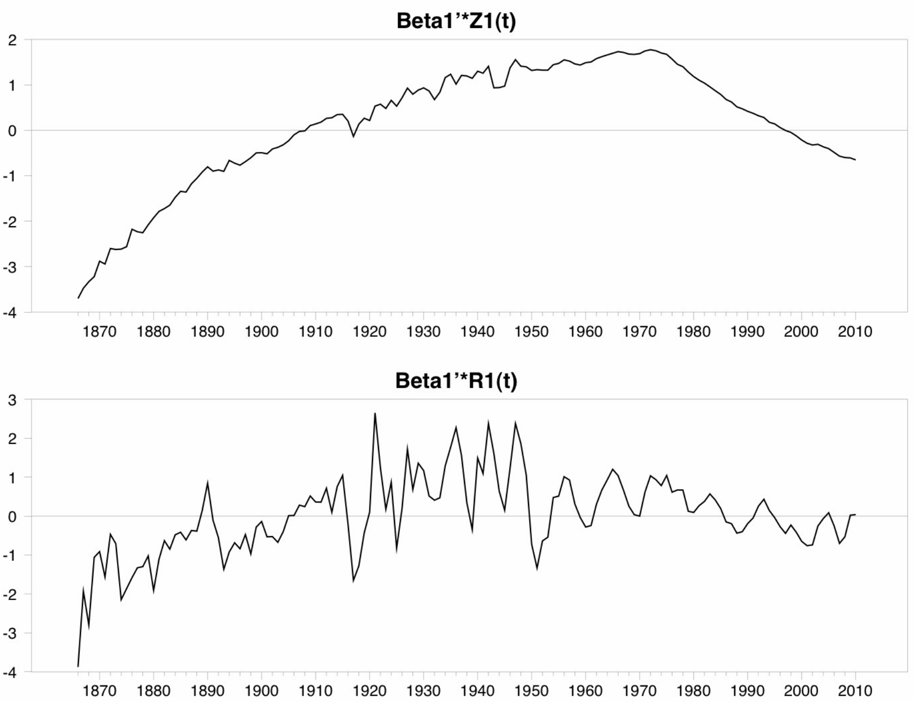
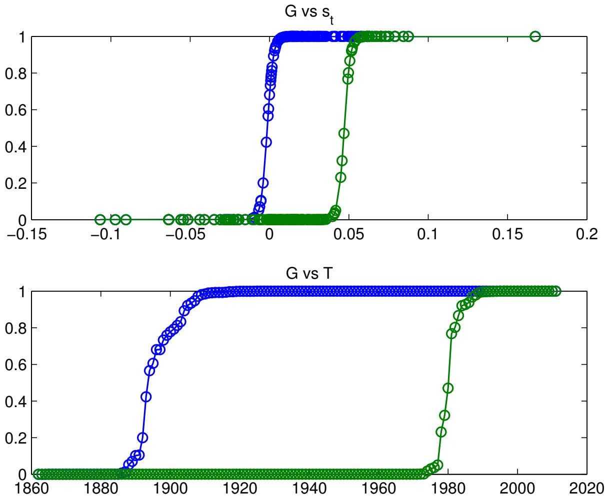
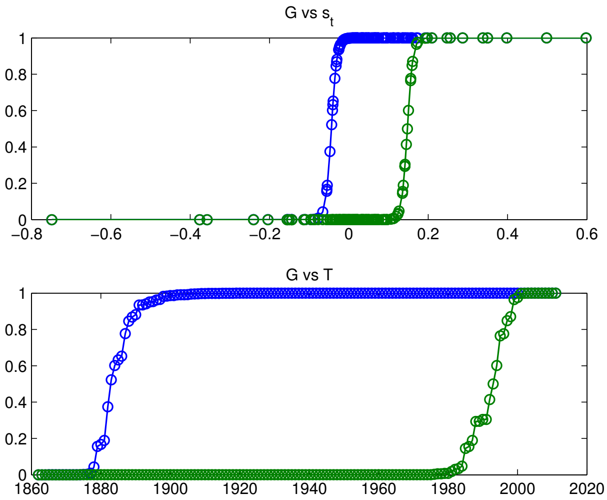


Figure 6: Estimated Transition Functions from MRSTAR model

(a) *GDP*



(b) CO_2



(c) *EI*

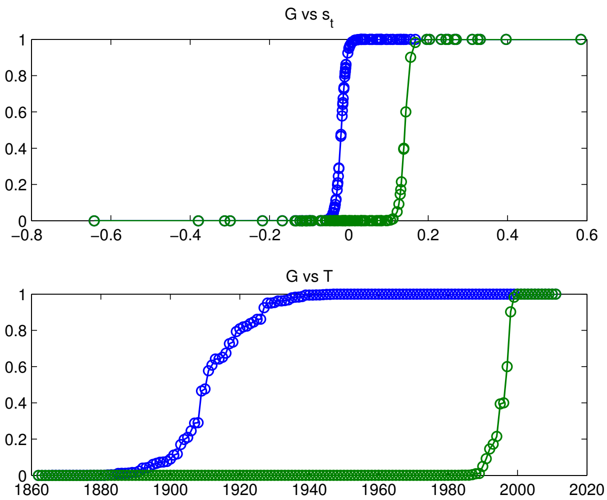


Figure 7: MS-VAR Results

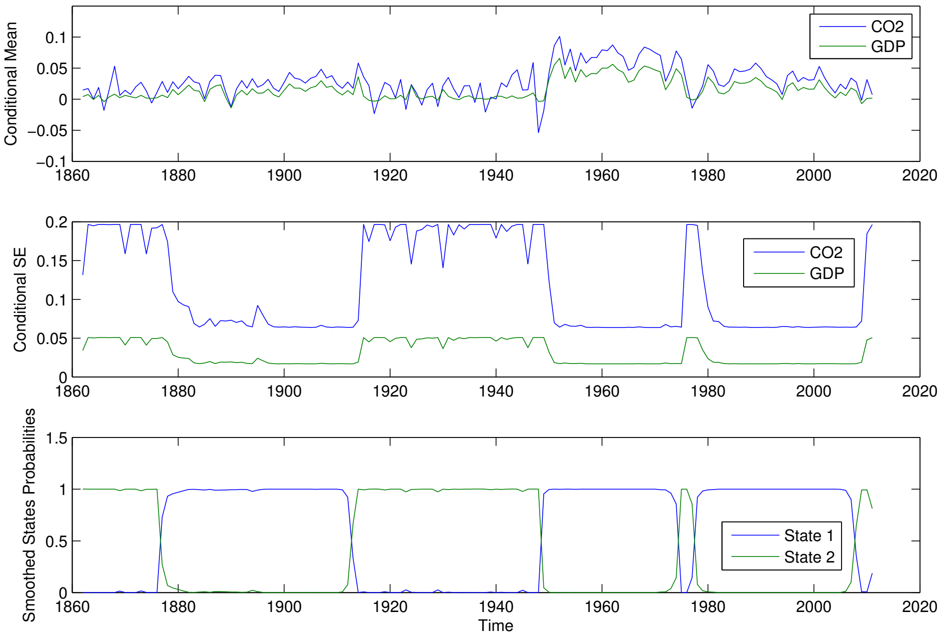


Figure 8: Fitted Quadratic Model

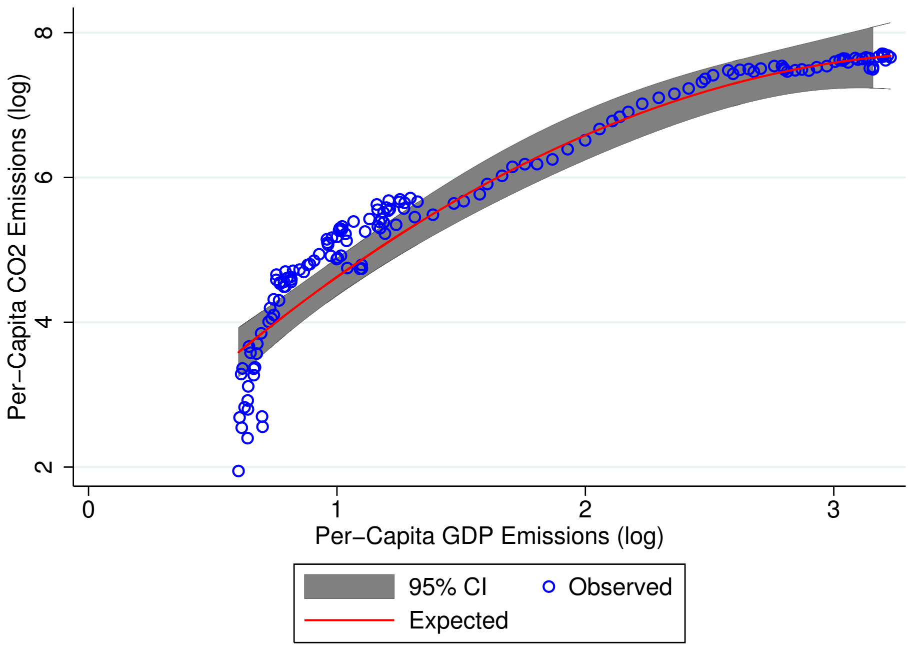


Figure 9: Quadratic Model Residuals

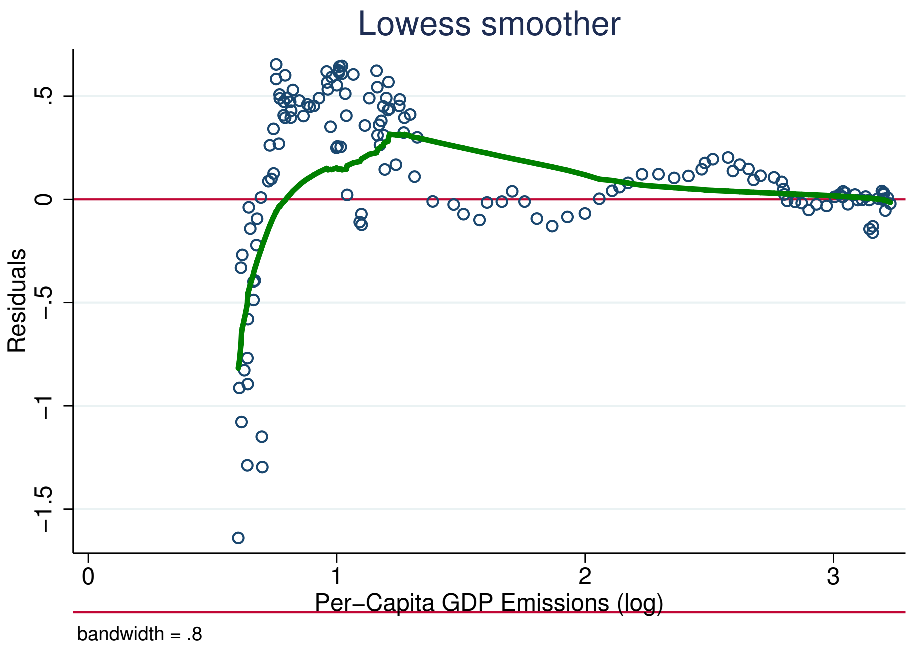


Figure 10: Fitted Cubic Spline

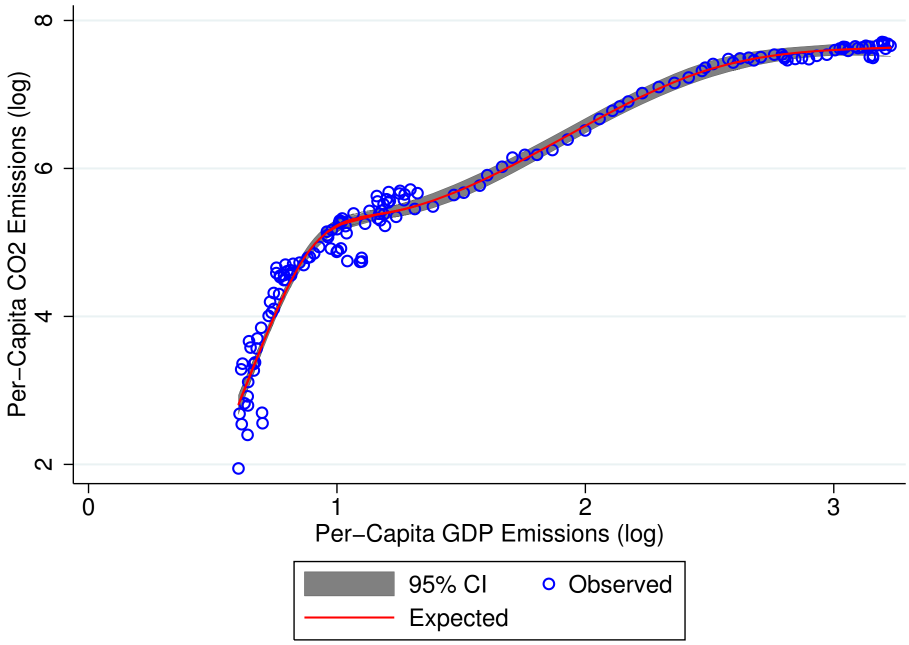
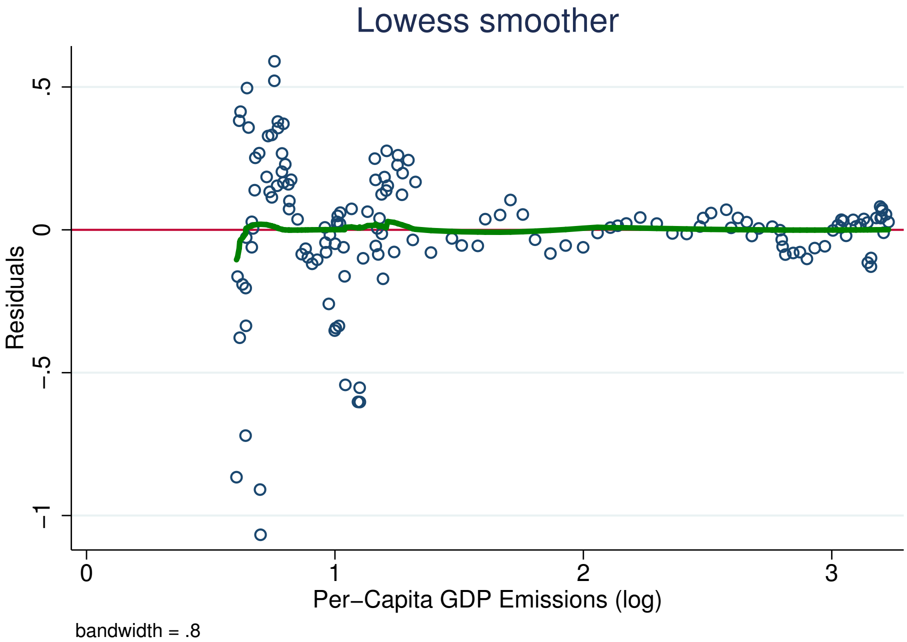


Figure 11: Cubic Spline Model Residuals



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