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Convergence in Road Transport CO_2 Emissions in Europe

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Abstract: In Europe the transport sector accounts for more than 27% of total CO_2 emissions and, within this sector, road transport is by far the largest polluter. This fact has placed road transport emissions abatement firmly on the agenda of global alliances. In this paper, we examine the convergence in per capita road transport CO_2 emissions in a sample of 22 European Union (EU) countries over the 1990-2014 period. We find evidence that EU countries converge to one another but depending on certain structural factors (conditional convergence), and that the convergence speed has increased over time. In light of this evidence, we estimate a conditional convergence dynamic panel data model to examine the structural factors affecting the convergence process and its influence on the convergence speed. Because, in our sample, road transport CO_2 emissions depend almost exclusively on (fossil) fuel consumption, we focus on the determinants channelled through the use of energy in the sector. By using alternative econometric approaches (pooled-OLS, fixed-effects and instrumental variables), our results show that the convergence process is conditioned by factors such as economic activity and fuel prices and that some of these factors have a significant effect on the convergence speed. These results may entail policy implications with regards to the geographical impact of the EU policies on climate change currently in place.

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1. Introduction

The International Energy Agency (IEA, 2018) has recently reported that transport sector CO_2 emissions from fuel combustion represented more than 27% of the total CO_2 emissions in the EU-28 in 2014. Road transport is the largest polluter, accounting for about 95% of transport sector CO_2 emissions. These figures are accompanied by a worrying trend: since 1990, total CO_2 emissions have fallen overall, while in transport, and especially in road transport, CO_2 emissions have risen (15% and 18%, respectively between 1990 and 2014), meaning that both sectors have heavily increased their relative shares.

There is an increasing concern about the negative externalities arising from the transport sector such as pollution, congestion, noise levels and those associated with the climate change. Recently, the Intergovernmental Panel on Climate Change (IPCC) reduced the limit temperature rise from 2 °C to 1.5 °C to prevent "severe, widespread and irreversible impacts globally" (IPCC, 2018). To keep the global temperature below this threshold, several "mitigation pathways" are required to eventually decrease the emission levels to zero (IPCC, 2014). Due to the fact that the road transport sector is still heavily dependent on fossil fuels, keeping the increase below 1.5°C would require complete decarbonization. As of 2016, the European Commission launched its low-emission mobility strategy (EC, 2016), stating that by 2050 transport GHG emissions "will need to be at least 60% lower than in 1990 and be firmly on the path towards zero". Although the Commission's strategy mentions the need to change mobility patterns (improvements in public transportation, multimodality, car sharing/pooling, etc.), its priority aims are based on fostering technological change throughout the Union. One of the main goals is to increase the efficiency of the transport system by investing in new digital technologies and alternative energy sources, and promoting zero-emission vehicles and related infrastructures. However, these plans are based on long-term forecasts that pay little attention to the geographical distribution of emission patterns (Aldy, 2006).

A proper way to analyse both the cross-country geographical distribution of emissions and their time variation is to consider a convergence framework.[1] In this study, we examine the convergence in per capita road transport CO_2 emissions, and the factors affecting the convergence process, among main EU countries. To the best of our knowledge, we are the first study that examines the convergence in this sector in Europe, despite its impact on climate change and prominence in the political agenda. In the first part of the paper, we analyse in detail this convergence process using the combination of different methodologies. In the second part, we show that road transport CO_2 emissions in Europe depend almost exclusively on energy (fossil fuel) consumption. Hence, we estimate a model for energy consumption given that this variable accounts for a sizable part in the dynamic of road transport CO_2 emissions. By doing that, we firstly identify those factors affecting the dynamics of CO_2 emissions channelled through the use of energy consumption in the road transport sector.

The concept of convergence emerges from the neoclassical growth literature, given the importance of establishing whether initially poorer countries tend to grow faster than initially richer ones. Convergence can be viewed in different ways. *Firstly*, the most widely used concept is that of β-convergence (Baumol, 1986). β-convergence is examined by testing whether there is a negative correlation between income growth and initial income levels for a group of countries. If the β-convergence hypothesis holds, then the poor countries grow faster and eventually tend to catch-up with the rich. In the long term, countries converge to the same level of income, known as steady-state or long-term equilibrium. In this situation, initial conditions are then irrelevant, because irrespective of the starting point, all countries converge

[1] See Johnson and Papageorgiou (2020) for an extensive and updated review on the different notions of convergence.

to the same ending point. This concept of convergence is known as absolute β-convergence, which implies convergence in levels.

The fact that initial conditions are irrelevant in the long-term implies that differences between countries are transitory, suggesting that the cross-section dispersion must decrease over time, a concept known as σ-convergence. However, there are situations where we can find β-convergence but not σ-convergence (Barro and Sala-i-Martin, 1992). For this reason, Friedman (1992) and Quah (1993) warned against committing Galton's fallacy due to absolute β-convergence can be observed even if there is constant or increasing dispersion over time.[2] One of these situations is, *secondly,* the presence of convergence but conditional on certain factors. Conditional (or relative) β-convergence implies that countries experience β-convergence but depending on their structural characteristics, such as the type of institutions, geographical or cultural characteristics, the existence of natural resources, etc. In this case, each country converges to its own steady state, meaning that countries only converge in long-run growth rates and they cannot converge to the same level unless their structural factors are equalized. Again, in the long term, initial conditions are not relevant, and the structural factors account for the long-run differences.

Finally, the concern on dispersion, introduced by the aforementioned concept of σ-convergence, leads to the concept of club convergence (Quah, 1993).[3] In this case, there is convergence among certain groups of countries that are similar not only in their structural characteristics but also in their initial conditions.[4] As noted by Durlauf and Johnson (1995), it is not easy to distinguish between conditional and club convergence using the standard tools of analysis in the neoclassical growth literature. From then on, a vast literature has tried to examine club convergence using different methods. One of these methods is the clustering approach proposed by Phillips and Sul (2007), that allows to evaluate a wide range of dynamics: divergence, club convergence and convergence (both absolute and conditional), and this is the method on which we rely to test for convergence in this paper.

These concepts of convergence –β-convergence, absolute and conditional, σ-convergence and club-convergence– can be straightforwardly adapted to study our per capita road transport CO_2 emissions series. For instance, in the case of conditional convergence, countries can converge between each other at a faster rate whenever structural differences between them are reduced. In the case of convergence clubs, some countries, due to their initial conditions, might have been trapped in a growth dynamic that do not allow them to catch up with other countries (see, e.g., Azariadis and Stachurski, 2005). In both cases, the consequence of conditional and club convergence is that some countries with high levels of emissions, and potentially low levels of economic activity, may never catch up with the leaders.[5] In terms of

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[2] For example, when there are random shocks that temporarily push the countries apart from the balanced growth path trajectory, and the dispersion at the initial period is lower than the variance of the shocks, the convergence process may not be accompanied by a reduction in the dispersion (Monfort, 2008).

[3] In the literature, we can also find the concepts of stochastic convergence and the distributional convergence approach, introduced by Carlino and Mills (1993) and Quah (1996), respectively. The former considers a time-series approach where convergence can be evaluated by means of unit root tests. The latter evaluates the time evolution of the cross-sectional distribution of the series and checks for aspects such as polarization and stratification.

[4] Club convergence is also defined as the tendency across countries to converge to multiple equilibria (also known as multiple regimes) depending upon the basin of attraction in which they begin, whereas, following Berthelemy (2006), in conditional convergence "there are multiple variants of the same equilibrium, parameterized by the conditioning variables". Also note that, inside each convergence club, absolute or conditional convergence can occur (see Phillips and Sul, 2009).

[5] To be precise, if there is a negative correlation between emission growth rates and initial levels, then we expect that countries with lower (higher) initial levels of emissions increase (reduce) emissions faster. Under this situation, all countries converge to the same level of per capita emissions in the long-term, but at different pace (absolute β-convergence). If this correlation holds conditional on certain structural characteristics of the economy, then each country converges to its own level of emissions, while sharing with the rest of countries the same growth dynamics

policy implications, this means that, unless there is a reversion in the unfavourable positions caused by different initial conditions or structural characteristics (see, e.g., the big push measures of Easterly, 2006) the emission abatement policies mentioned above can be unacceptable for certain countries, specially due to the close relationship between emissions and economic activity paired with the high cost of clean transport technologies (Santos, 2017). Particularly, in our work, we find evidence of conditional convergence among the countries of our sample. This implies, in terms of the geographical distribution impacts of the abatement policies that are being carried out in the EU, that it is very relevant to know which factors are conditioning the convergence process of the countries.

Specifically, in the first part of the paper, we examine the convergence in per capita road transport CO_2 emissions for a panel data set of 22 European countries over the period 1990-2014. To do that, we test the concepts of β, σ and club convergence. Initially, we examine these concepts using neoclassical growth regressions. Then, since these regressions suffer from several biases (e.g. Nickell, 1981) and because of the difficulty of distinguishing between conditional β-convergence and club convergence, we rely on the methodology proposed by Phillips and Sul (2007) to discriminate between absolute, conditional and club convergence hypotheses. We reach the following main results. First, the null hypothesis of club convergence is rejected, while we find evidence of σ-convergence (reduction in the disparities) paired with conditional β-convergence during the period under study. Moreover, we find that the convergence speed has increased over time. In the second part of the paper, we estimate a conditional convergence dynamic panel data model for energy consumption in the road transport sector. Due to traditional econometric approaches (e.g., pooled-OLS and fixed-effects estimates) may suffer from endogeneity problems, we also consider an instrumental variable approach. Our results indicate that economic activity, fuel prices, passenger car usage intensity (proxy by passenger cars relative to GDP) and relative freight traffic (traffic of goods relative to the traffic of passengers) are factors that, through fuel consumption in the sector, affect the convergence process of per capita road transport CO_2 emissions in Europe. Further, by specifying interaction terms in the model, we find that the growth rates of some of these factors (GDP, fuel prices and car usage intensity) also have a significant effect on the convergence speed.

The rest of the paper is organized as follows. In Section 2, we present a brief literature review on convergence and determining factors of transport CO_2 emissions. In section 3, we conduct the convergence analysis of road transport CO_2 emissions over the sample considered. In Section 4, we motivate the use of an energy model to study the determinants of emissions, present the conditional convergence dynamic panel data model, describe the main variables in the database and show the estimated results using alternative econometric approaches. Finally, Section 5 concludes.

2. Literature review

There is a vast body of research that have sought to explain the factors determining emissions in the transport sector. This research can be classified according to the method used. Some authors have used decomposition techniques based on certain mathematical identities. For instance, for transport CO_2 emissions, Lakshmanan and Han (1997) found that the main factors determining CO_2 emissions in the US are the growth in the propensity to travel, population, and GDP. For a group of Asian countries, Timilsina and Shrestha (2009) found that the main underlying factors are energy intensity in the sector, population growth and GDP. Focusing on

(conditional β-convergence). Under club convergence, each club converges towards its own long-run equilibrium, which is determined by the initial conditions, so the growth dynamics can differ among clubs.

the passenger car sector, Kwon (2005) found that the distance travelled per person was the dominant force for the growth of emissions over a period of 30 years.

Other authors, more in line with our study, use regression models (time series or panel data analysis). For example, Begum et al. (2015) show for Malaysia that energy consumption and GDP have a long-term positive impact on total emissions, whereas population growth is neutral. Yang et al. (2015) analyse the evolution of transport sector emissions in China, highlighting the relevance of the Chinese socio-economic development and the rise in income. Regarding the road transport sector emissions, Shu and Lam (2011) estimate the emissions for geographical grid-cells at county level in the US using multiple linear regression models, considering population density, urban area, income and road density as determinants. Using the same method, Mustapa and Bekhet (2015) show that fuel price, fuel efficiency and distance travelled are the main factors determining emissions growth in Malaysia. Saboori et al. (2014) analyse the long-run relationship between emissions, energy consumption and economic growth in OECD countries and conclude that most of the emissions derive from energy consumption rather than from economic growth. Regarding the passenger car sector in Europe, Ryan et al. (2008) evaluate the effect of fiscal policy on passenger car sales and emissions, and González et al. (2019) provide evidence that technological progress and fuel efficiency are negatively associated with emissions while economic activity, motorization rate and the tax policy favouring diesel cars are positively associated. Also, for passenger cars, but in this case for Spain, González and Marrero (2012) find a negative effect on CO_2 emissions caused by dieselization, which is more important than the improvements in fuel efficiency.

In relation to the literature of convergence in emissions, many studies have focused their attention on total per capita CO_2 emissions (see Marrero, 2010, and references therein). Using a long time period (1960-2000), Aldy (2006) finds convergence between 23 OECD countries and divergence in a global sample of 88 countries not only for the period considered but for the next 50 years. Applying the concept of stochastic convergence, Romero-Ávila (2008) finds strong evidence of convergence in CO_2 emissions between 23 industrialized countries over the period 1960-2002. Following a distributional approach, Ezcurra (2007) studies the time evolution of the cross-section distribution of per capita emissions of 87 countries between 1960 and 1999 and finds evidence of convergence due to a reduction in cross-country disparities. Testing for absolute convergence and allowing different speeds for each country, Jobert et al. (2010) find evidence of convergence between 22 European countries over 1971-2006. Reviewing this literature, Pettersson et al. (2014) conclude that, even though the results are very sensitive to the dataset and the econometric method used, there is a general pattern of convergence between OECD countries.

Fewer studies have been carried out to analyse the convergence in emissions in the transport sector. Apergis and Payne (2017) examined club convergence of per capita emissions in 50 U.S. states in the aggregate and by sector, including transport. They find two convergence clubs in total emissions and greater polarization in the transport sector (three clubs). Wang and Zhang (2014) analyse convergence in per capita CO_2 emissions in six sectors, including transport, from 199 to 2010 across 28 provinces in China, and report σ-convergence in the aggregate and conditional β-convergence in the transport sector. Mishra and Smyth (2017) examine stochastic convergence at the sector level in Australia over the period 1973-2014. They provide evidence on convergence in all sectors, except for transport, arguing that the low energy efficiency in this sector is due to the higher investment in roads and less in railways, public transport, and alternative fuel energies. By contrast, Ivanovski et al. (2018), also considering Australian regions over the period 1990-2016, find one convergence club and one divergent region in the transport sector. The authors attribute this relatively strong evidence of convergence to the coordinated Australian policy on fuel economy standards, fuel taxation, subsidies for electric vehicles and improvements in public transportation.

After reviewing this related literature, we have not found studies that have addressed the convergence problem in CO_2 emissions in the road transport sector in Europe, thus our study is a relevant contribution to the existing literature.

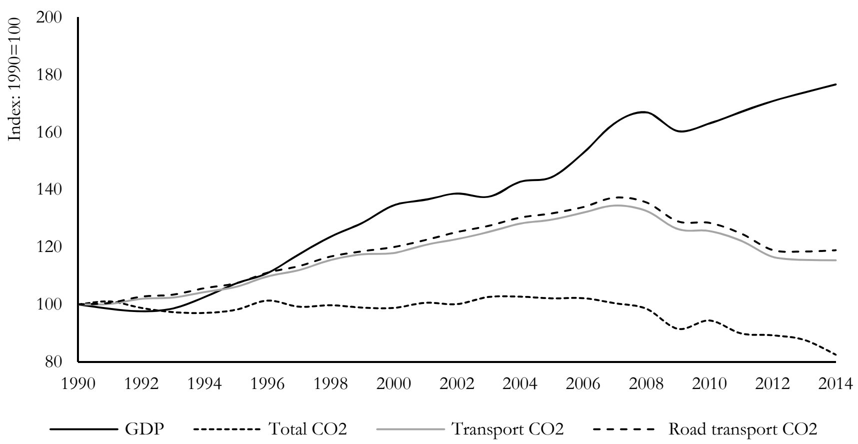
3. Convergence in Road Transport CO_2 Emissions in the EU

In this section, we examine the β, σ and club convergence hypotheses in per capita road transport CO_2 emissions[6] from 1990 to 2014 for 22 EU countries: Austria, Belgium, Croatia, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom. We have selected the longest time period and the greater number of European countries, subject to data availability in the data sources (see Table A1 in Appendix A). Subsection 3.1 shows preliminary evidence of convergence and the methodology to test for β, σ and club convergence hypotheses. Subsection 3.2 shows the estimation results of these convergence hypotheses.

3.1 Preliminary evidence and methodology

For the 22 EU countries, Figure 1 shows the sample average of per capita GDP jointly with per capita CO_2 emissions for all the sectors of the economy (total), for the transport sector and for the road transport sector. To compare growth dynamics, the values in 1990 have been normalized to 100.

Figure 1. Trends of per capita GDP and CO_2 emissions (total, transport and road transport) in the EU (Index 1990=100)



Note: Prepared by authors

In view of Figure 1, we highlight that road transport emissions have increased during the period: the average level in 2014 (1.73 tonnes of carbon per person) is 18.8% higher than the average level in 1990 (1.46 tonnes of carbon per person). Second, it shows that there is a period of decrease in emissions following the recession in 2007, and a slight increase at the end of the time series likely due to the recovery after the crisis. Third, we see that the growth

[6] Road transport CO_2 emissions from fuel combustion contains the emissions arising from fuel use in road vehicles, including the use of agricultural vehicles on highways. Road vehicles include all motorized vehicles that travel in public roads and it is expressed in million tonnes of carbon (Mt CO_2). It comprises, among others categories, passenger cars, motorcycles, buses and trucks (IEA 2018). The definition of passenger cars refers to “a road motor vehicle intended for the carriage of passengers and designed to seat no more than nine persons (…) and the term also covers microcars, taxis and other hired passenger cars” (SE Eurostat, 2020).

dynamic of transport emissions closely follows that of road transport emissions. On average, the road transport sector accounts for more than 90% of the transport sector during the period. Fourth, the growth of the road transport sector between 1990 and 2014 is higher than the growth of the transport sector (18.8% and 15.4%, respectively), meaning that the relative share of road transport emissions in transport emissions rose from 91% in 1990 to 94% in 2014. Fifth, in view of the diverging trends of transport emissions and per capita GDP especially after 2007 (per capita GDP has grown, on average, 76.6% between 1990 and 2014), the decline in transport emissions after this period does not seem to be entirely related to the decline in economic activity. Finally, the downward trend in total CO_2 emissions (on average, it has decreased about 17.5% in the entire period) implies that the relative share of both transport as a whole and road transport in total emissions has increased and explains why transport emissions abatement is currently one of the main targets of climate policies.

To measure (absolute) β-convergence in road transport CO_2 emissions, we specify a neoclassical growth regression model for emissions using a panel data specification. Therefore, the change of the log level of road transport CO_2 emissions per capita (y_{it}) for a country *i* at time *t* can be expressed as:

$$\Delta\ln(y_{it}) = \alpha + \rho \ln\left(y_{i,t-1}\right) + \varepsilon_{it} \, , \tag{1}$$

where ρ is an autoregressive parameter related with the speed of convergence and ε_{it} is an error term that we assume to be i.i.d. and normally distributed. Evidence of β-convergence implies a negative relationship between the growth rate of emissions and the initial levels, thus requiring a negative and significant ρ parameter. Note that the parameter ρ is not directly the speed of convergence. In this setting, the speed of convergence is defined as $\beta = -\ln(1+\rho)$. An alternative way to measure the speed of convergence is using the half-life, i.e., the time required by a country to cover a half of the distance to the steady state, which is given by $-\ln(2)/\ln(1+\beta)$. For the panel data specification of equation (1) to be valid, two conditions are called for: $\Delta\ln(y_{it})$ must be stationary and the autoregressive parameter ρ must be common to all countries.

With respect to the first condition, the presence of a unit root in road transport emissions, $\ln(y_{it})$, would imply that shocks are permanent so that growth rates are not mean reverting. By contrast, if road transport emissions follow a stationary process, shocks have a transitory impact, allowing to make inference based on the past behaviour of the series. Additionally, β-convergence implies that emissions converge to its steady state at a positive and uniform rate across countries, thus unit root tests and β-convergence are testing the same hypothesis (Michelacci and Zaffaroni, 2000).[7]

To test for stationarity, we use the unit root tests of Levin-Lin-Chu (2002) and of Im-Pesaran-Shin (2003), LLC and IPS, respectively. The null hypothesis of both tests is that all the panels contain a unit root versus the alternative that some series are stationary. The difference between LLC and IPS is related with the second condition that we have to check: the heterogeneity in the autoregressive coefficient. LLC considers homogenous autoregressive coefficients whereas IPS relaxes this assumption by allowing heterogenous coefficients (ρ is different for each country in equation 1). Table 1 shows the results (statistic and p-value associated) of the LLC and IPS tests for the series in levels and in first differences.

[7] Note that unit root tests consider an autoregressive model in the form $y_t = \alpha + \delta \; y_{t-1} + \varepsilon_t$ and then fit the model $\Delta y_t = \alpha + \underbrace{(\delta - 1)}_{\rho} y_{t-1} + \varepsilon_t$ to test if $\delta = 1$, which is equivalent to test $\rho = 0$ in our equation (1).

Table 1. Panel unit root tests of per capita road transport CO_2 emissions

	LLC		IPS	
	Statistic	**p-value**	**Statistic**	**p-value**
Level	-2.81	0.0025	0.13	0.5535
First difference	-9.79	0.0000	-9.75	0.0000

Note: Prepared by author. For the LLC and IPS, the adjusted-t and W-t-bar and are reported, respectively. All the tests include the intercept and the number of lags was chosen according to the AIC information criteria

The results in Table 1 confirm that the panel series in first differences are stationary. However, since the null hypothesis in these tests can be rejected if only one of the series in the panel is stationary, we complement the analysis with a visual inspection of the series. In Figure B1 in Appendix B, we show, for each country, the log of road transport CO_2 emissions per capita and its first difference (growth rate). We can see that the growth rates are stable over the entire time period. Therefore, the unit root tests and the visual inspection ensure the validity of equation (1) in terms of stationarity.

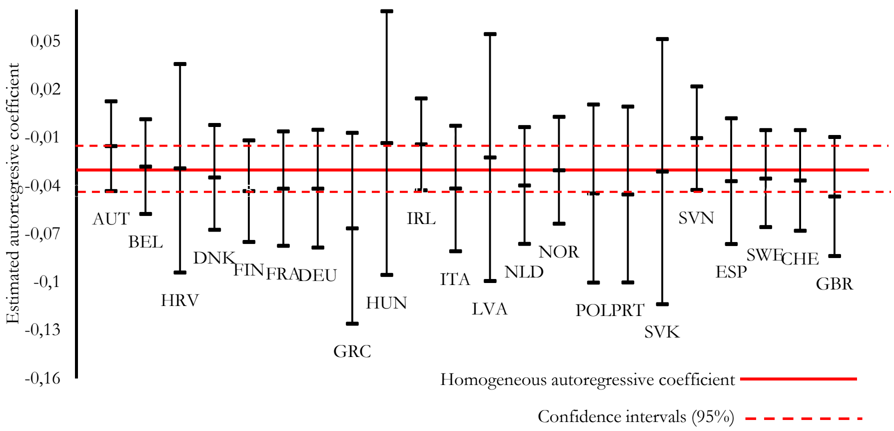
With respect to the second condition (homogeneity of ρ in (1)), we estimate an unrestricted model assuming heterogeneous (country-specific) autoregressive coefficients (i.e., allowing ρ_i to differ across countries), and a restricted model assuming a homogenous (common to all countries) coefficient ρ. Then, using a F-Statistic of residual differences, we test the null hypothesis that the ρ_i coefficients are all equal. The estimation results (see Table A2 in Appendix A) show that the F-Statistic (0.50) is lower than the critical value (1.58), with a corresponding p-value of 0.97. Thus, we cannot reject the null hypothesis of homogeneity of the ρ coefficients across countries in the sample. We can visualise this result in Figure 2, where we show the point estimates and confidence intervals of the estimated autoregressive coefficients ρ_i for each country. We also show the point estimated and the confidence interval of the (homogenous) ρ for the restricted model. We can see that the point estimates are not significantly different between each other, even in the case of Greece (GRC), which is the country with a more heterogeneous behaviour.[8]

Once we are confident about the validity of the panel data specification in (1), we first provide a basic intuition of β-convergence in our sample. Figure 3 shows the cross-section correlation between the annual growth of emissions over the 1990-2014 period and the initial level of emissions in 1990. The negative and significant slope in the graphic is an evidence of absolute convergence, suggesting that countries with lower (higher) initial levels of CO_2 emissions are increasing (reducing) their emissions faster. The graph helps to understand, for example, the rapid growth of Poland (3.6% per year), rising from 0.47 to 1.10 tonnes of carbon per person, and of Croatia (2.6% per year), from 0.67 to 1.15 tonnes of carbon per person. It also helps explain the good performance of Finland and United Kingdom in the period, with annual reductions of 0.65% and 0.43%, respectively.

However, despite its relatively high goodness of fit ($R^2 = 0.66$), the relationship fails to account for cases such as Slovenia or Ireland, both with high initial levels of emissions and with annual growth rates higher than 2% during the period. This heterogeneity points to the possibility of conditional or club convergence among countries. Oversimplifying, the countries can be graphically grouped in parallel straight lines, meaning conditional convergence with the same growth dynamics or in lines with different slopes, meaning club convergence with different growth dynamics.[9]

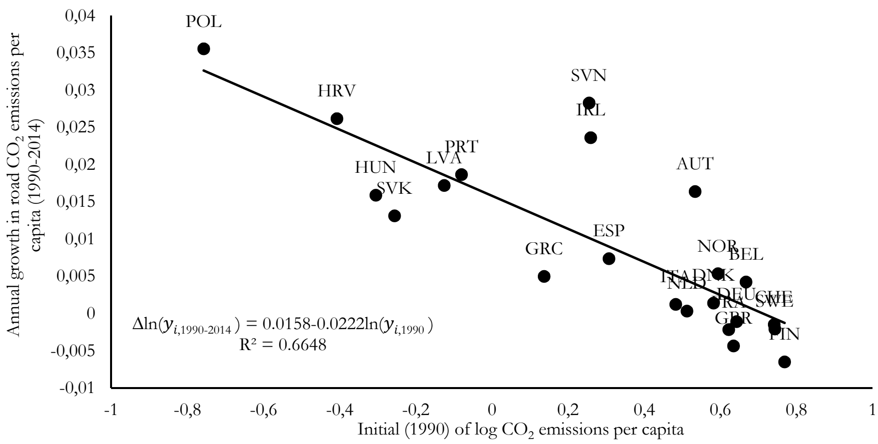
[8] In a previous analysis, we remove Estonia from the sample due to a significant heterogeneous behaviour relative to the rest of countries, which will constitute a big outlier in our posterior regressions.
[9] An example of this graph can be consulted in Johnson and Papageorgiou (2020), page 137.

Figure 2. Country-specific autoregressive coefficients



Note: Prepared by authors

Figure 3. β-convergence of per capita road transport CO_2 emissions in the EU



Note: Prepared by authors. Data from IEA (2018)

Following with this preliminary analysis, the next issue we explore is whether the dispersion in the cross-section distribution has fallen during this period, i.e., σ-convergence. Following Ram (2018), to measure σ-convergence, we first need to compute the sample variance of the log of road transport CO_2 emissions per capita across countries at time *t* as:

$$\sigma_t^2 = \left(\frac{1}{N}\right)\sum_{i=1}^{N}[ln(y_{i,t}) - \mu_t]^2 \,, \tag{2}$$

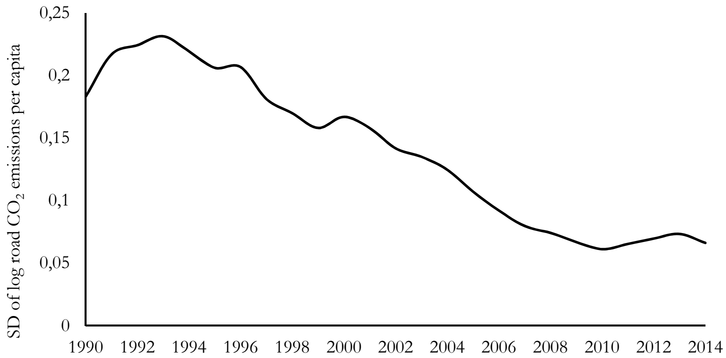
where μ_t is the sample mean of $ln(y_{i,t})$ and N is the number of countries. To see whether the cross-country dispersion increases or decreases during the period, we calculate the annual rate of change of σ_t^2 using the following expression:

$$\ln(\sigma_t^2) = \varphi + \theta t + u_t \,, \tag{3}$$

where φ is a constant, the slope θ denotes the growth rate of a linear trend, t is the time variable and u_t is an error term. The annual exponential rate of change of σ_t^2 can be calculated as $(e^{\theta} - 1)$.

Figure 4 shows the evolution of the standard deviation of the log of road transport CO_2 emissions per capita over time. Clearly, there is a reduction in the disparities between the countries during the period: the standard deviation in 2014, which is 0.06, is 66% lower than the standard deviation in 1990, which is 0.18. The reduction in the dispersion is not uniform. For instance, there is a period at the end of the series where the dispersion increased, matching with the economic crisis highlighted in Figure 1. However, according to the previous stationary analysis, these shocks were not permanent, and the series reverted again to the mean after a reduced number of years. Thus, for the 22 EU countries considered in our sample, we can see that there is a strong evidence in favour of σ-convergence between 1990 and 2014.

Figure 4. σ-convergence of per capita road transport CO_2 emissions in the EU



Note: Prepared by authors. Data from IEA (2018)

Next, we present the approach to examine the possibility of convergence clubs. Distinguishing between conditional β-convergence and club convergence has been a difficult task (Islam, 2003). In this paper, we use the convergence test developed by Phillips and Sul (2007) (henceforth, PS), which allows us to evaluate a wide range of dynamics, such as divergence, club convergence and convergence (both absolute and conditional).[10] Following PS, we first decompose the per capita road transport CO_2 emissions according to the following panel data equation:

$$\ln(y_{it}) = \delta_{it}\mu_t \,, \tag{4}$$

where μ_t is a growth component that is common among countries and δ_{it} is an idiosyncratic component that varies over time. Therefore, the time-varying loading factor δ_{it} represents the transition path of country *i* in relation to the common steady-state trend μ_t. Different idiosyncratic characteristics related to technology, institutions or energy policies are reflected in the diverse shapes of the economic transition encompassed in δ_{it}. To implement the statistical test, we now define the following relative transition coefficient (h_{it}):

$$h_{it} = \frac{\ln(y_{it})}{\frac{1}{N}\sum \ln(y_{it})} = \frac{\delta_{it}}{\frac{1}{N}\sum \delta_{it}}\,, \tag{5}$$

which eliminates the common trend μ_t by scaling the component δ_{it} in relation to the cross-section average. The transition parameter measures both the country behaviour relative to the average and the country deviations from the common growth path. We also need to assume a general form for the loading component δ_{it} in equation (4):

[10] Other alternatives to test for club convergence, using for example ex-ante criteria to group countries (Durlauf and Johnson, 1995; Desdoigts, 1999) or leaving the determinants of club formation unspecified (Bernard and Durlauf, 1995; Hobijn and Franses, 2000), are not able to test simultaneously for the different types of convergence (or divergence) processes, as PS does.

$$\delta_{it} = \delta_i + \sigma_{it}\varepsilon_{it} \; ; \sigma_{it} = \frac{\sigma_i}{L(t)t^{\alpha}} \; ; \text{ for } t \geq 1 \quad \sigma_i > 0 \, . \tag{6}$$

where ε_{it} is independently and identically distributed (0,1), $L(t)$ is a slowly varying function of time (equal to $ln(t)$ in the application) and α is the speed of convergence. From equation (6), the null hypothesis of convergence implies that $\delta_i = \delta$ for all *i* and $\alpha \geq 0$, while the alternative corresponds to either overall divergence ($\delta_i \neq \delta$ for all *i* or $\alpha < 0$) or club convergence ($\delta_i = \delta$ for some *i* and $\alpha \geq 0$).

From equation (5), convergence implies that $h_{it} \rightarrow 1$ as $t \rightarrow \infty$ for any country *i*. In this case, the cross-sectional variance of h_{it} under the null hypothesis, $\sigma_t^2 = \frac{1}{N}\sum_{i=1}^{N}(h_{it}-1)^2$, must tend to zero. In fact, this property and definition of σ_t^2 is the one used by PS to prove that testing for absolute convergence is equivalent to using a one-sided test for the estimated $\hat{b}$ coefficient in the following *log-t* regression (see Appendix B in PS for details):

$$\log\left(\frac{\sigma_1^2}{\sigma_t^2}\right) - 2logL(t) = \hat{a} + \hat{b}\log t + \widehat{u_t} \;\; for \; t = [rT], [rT]+1, \ldots, T \; with \; r > 0 \, , \tag{7}$$

where σ_1^2/σ_t^2 is the cross-sectional variance in the initial period in relation to the variance of each time period, $\hat{a}$ is an intercept, $\hat{b} = 2\hat{\alpha}$, $\widehat{u_t}$ is an error term and r is a fraction to disregard the first r% of the time series, which is shown by PS to benefit the power of the convergence tests.[11] Since $\hat{b}$ is a scalar, the null hypothesis of convergence is tested using a one-sided t-test for the parameter $\hat{b}$ using HAC standard errors. If $t_b < -1.65$ (at 5% significance level), the null hypothesis of absolute convergence is rejected, on the understanding that a rejection of the null hypothesis does not imply absence of convergence between subgroups of countries.[12] In our case, we are not only interested in the sign of the coefficient $\hat{b}$ but also in its magnitude because it measures the speed of convergence. Values of $\hat{b}$ equal to or larger than 2 imply absolute β-convergence, and values in the range $2 \geq \hat{b} \geq 0$ imply conditional β-convergence.

3.2 Convergence estimation results

Table 2 summarizes our results of convergence in per capita CO_2 emissions in road transport in Europe. The table shows the estimates of β, σ and club convergence according to equations (1), (3) and (7). In the case of β-convergence, the significance of the ρ parameter indicates the existence of absolute convergence, showing that countries are converging to the same level of CO_2 emissions in the long term with an associated speed of 3% per year. This implies that countries have covered half the distance to the steady state in 23 years (half-life measure). In relation to σ-convergence, the reduction of the dispersion at an average rate of 5.9% per year reinforces the result already shown in Figure 4.

Despite the fact that there is evidence of absolute convergence, this result may be spurious, since we are not taking into account country fixed effects, time effects or other unobservable variables. Indeed, looking at the estimates of the log-t regression of PS, the fact that the estimated b-coefficient in (7) is lower than 2 indicates the existence of conditional convergence, as commented at the end of Section 3.1. Hence, countries with lower (higher) initial levels of emissions are increasing (reducing) emissions faster, but conditional on structural and specific characteristics of each country. Besides this, the PS methodology indicates that there are no groups of countries with similar structural characteristics and initial

[11] They recommend r=1⁄3 for T<50.

[12] Indeed, the testing procedure in PS is embedded within a clustering algorithm for detecting convergence clubs. When starting the algorithm, whether or not a country is assigned to a particular convergence club depends precisely on the outcome of the one-sided t-test of $\hat{b}$ in the log-t regression performed for different sub-samples.

conditions different than the rest (convergence clubs), a result that can be probably explained by the homogeneity of our sample (developed countries from the EU). In spite of that homogeneity, the evidence found is of conditional convergence and not of absolute convergence. Accordingly, in the remainder of the paper we focus on a conditional-convergence specification of equation (1), including country-fixed effects, i.e., the constant term α is country-specific, α_i.

Table 2. β-, σ- and club-convergence estimation results

Time period	1990-2014
Absolute β-convergence	
Autoregressive coefficient ρ	-0.0297 (-5.20)
Speed of convergence (%): $\beta = -\ln(1+\rho)$	3.01%
Half-life (years): $-\ln(2)/\ln(1+\beta)$	23.34
σ-convergence	
Annual Rate of Change (σ_t^2)	-0.0596 (-15.53)
log-t regression (Phillip and Sul, 2007)	
b coefficient	0.8027 (45.26)

Note: Prepared by authors. t-statistics in parentheses. Note that these are pooled-OLS estimations

Our last analysis concerns the potential changes in the speed of convergence. Thus, we analyse whether the autoregressive parameter ρ has changed over time or has remained more or less constant during the entire period. To check this in a very intuitive way, we modify equation (1) to include, in addition to the country-specific intercept α_i, a time interaction term (t) with the lag of road transport CO_2 emissions per capita as follows:[13]

$$\Delta\ln(y_{it}) = \alpha_i + \tau_t + \rho_1\ln(y_{i,t-1}) + \rho_2\ln(y_{i,t-1})\,t + \varepsilon_{it}\ , \qquad (8)$$

where, in this case, the autoregressive parameter ρ is now $\rho_1 + \rho_2\, t$, where t takes values from 0 to 24 in our sample, and τ_t is a common time effect. In Table 3, we show estimations results of alternative versions of (8). In all cases, we always incorporate time effects in order to control for common time factors related, for example, to the technological progress in the transport sector or to common international oil price effects. Not including these time fixed effects would bias our estimates. Models 1 and 2 do not include the interaction term, while models 3 and 4 include the $\rho_2\ln(y_{i,t-1})\,t$ term. Models 2 and 4 include country fixed effects, while models 1 and 3, which are presented just for illustrative purposes bearing in mind the previous evidence of conditional convergence, do not include country fixed effects. For estimation results of models 3 and 4, Figure 5 shows the evolution of the ρ parameter between 1990 and 2014.

First, we find that the convergence speed is, as expected, higher for the conditional convergence models including country fixed effects (Model 2 and 4) than for the absolute convergence models (Model 1 and 3). This means that countries are converging more rapidly to their own potential steady-state equilibrium of per capita emissions (within convergence – or conditional convergence) than to a potential common (average) level of emissions (between convergence – or absolute convergence). The second relevant finding is that the interaction parameter (ρ_2 in (8)) is negative and significant in models 3 and 4, indicating that there is an upward trend (in absolute value) of the convergence speed between 1990 and 2014 (Figure 5).

[13] We also tested a quadratic interaction term to account for a non-linear time effect, but it was not significant.

Similar results have been reported by other authors, such as Monfort (2008), who found that the convergence speed in per capita GDP among European countries accelerated for periods before and after the 1980s. For example, according with our estimates of Model 4, the convergence speed, β, and the half-life coefficients are, approximately, 6% and 12 years in 1990, and 25% and 3 years in 2014.

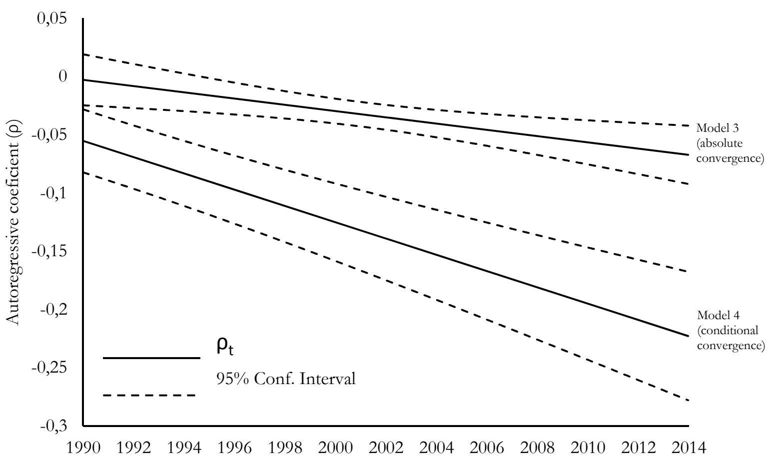
Summing up, in this section we can conclude that there is strong evidence of a reduction in the disparities (σ-convergence) and of a conditional β-convergence process, with a progressive acceleration over time of the convergence speed, in per capita road transport CO_2 emissions between 1990 and 2014 for the 22 EU countries analysed. In light of this evidence, the next question is to identify some of the factors that can determine the dynamic of the CO_2 emissions and to assess their impact on the convergence speed.

Table 3. Time-varying autoregressive coefficient models

Dependent variable: Annual growth rate of per capita road transport CO_2 emissions				
	Model 1	**Model 2**	**Model 3**	**Model 4**
Constant	0.0266**	0.0705***	0.0163	0.0948***
	(-2.01)	(-3.98)	(-1.17)	(-5.90)
Lag of road transport CO_2 emissions per capita (log)	-0.0297***	-0.0611***	-0.0029	-0.0553***
	(-5.2039)	(-4.135)	(-0.2587)	(-4.0079)
Lag of road transport CO_2 emissions per capita (log) x Time			-0.0027***	-0.0070***
			(-3.0112)	(-6.6658)
Country Fixed Effects	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
N	496	496	496	496
adj. R-sq	0.2927	0.3587	0.3118	0.4513

*Note: Prepared by authors. t-statistics in parentheses. * p<0.10 *** p<0.0.05 *** p<0.01*

Figure 5. Time-varying autoregressive coefficient



Note: Prepared by authors. Data from IEA (2018)

4. An Energy Consumption Model: Determinants of Road Transport CO_2 Emissions and its Influence on the Convergence Speed

In this section, we present the empirical framework and the dataset to analyse the determinants of road transport CO_2 emissions, and its influence on the convergence speed. As we motivate next, we focus on the determinants channelled through the use of energy (fuel consumption) in the sector.

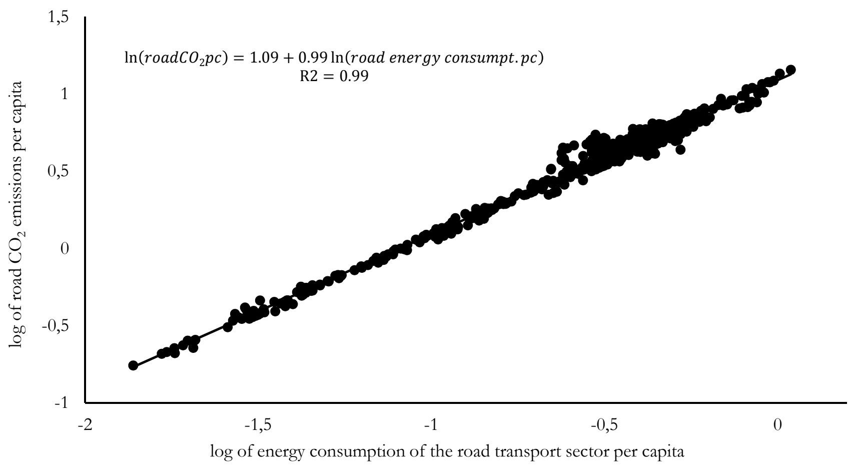
An important body of literature has studied the determinants of total CO_2 emissions (e.g., Ang, 2007; Jalil and Mahmud, 2009; Acaravci and Ozturk, 2010; Marrero, 2010). In these studies, total CO_2 emissions are expressed as a function of energy consumption (or energy intensity) and per capita GDP, including in some cases the square of the GDP to test for the environmental Kuznets curve hypothesis (see, e.g., Esteve and Tamarit, 2012). Moreover, according to Marrero (2010), the relationship between total CO_2 emissions, GDP and energy is far from exact, because the impact of energy consumption on overall CO_2 emissions depends on the primary energy mix (i.e., the combination of different primary energy sources such as coal, oil, gas, nuclear and renewable) and on the distribution of the final use of energy (i.e., industry, services, households or transport). Thus, for overall emissions, energy consumption is fundamental, but it is not the only factor affecting them.

However, for the road transport sector in Europe, we find that CO_2 emissions depend almost exclusively on energy (fossil fuel) consumption.[14] Figure 6 shows the log of per capita energy consumption in the road transport sector on the x-axis, and the log of per capita road transport CO_2 emissions on the y-axis. The graphic reveals that, in our sample, a 99% of the variability in per capita road transport CO_2 emissions can be accounted by the variability in per capita energy (fuel) consumption. Moreover, the slope is equal to one (that the slope is equal to one cannot be rejected at a 0.1% level of significance). Therefore, for our set of EU countries between 1990 and 2014, the dynamic of road transport CO_2 emissions is almost fully explained by the dynamic of energy (fuel) consumption. In consequence, we specify an energy (fuel) consumption model assuming that, at the aggregate macro level in the sector, the effect of the explanatory variables on CO_2 emissions is channelled through the use of fuel.[15]

Figure 6. CO_2 emissions and energy consumption in road transport in the EU

[14] Total energy consumption of the road transport sector includes "all the energy consumed by road vehicles, including agriculture and industrial trucks, household cars and motorcycles, commercial and government vehicles" (ODYSSEE, 2018b) and is measured in million tonnes of oil equivalent (Mtoe).

[15] The progressive introduction of electric vehicles can potentially change this almost exact relationship between CO_2 emissions and fuel consumption, especially if they are powered by renewable energy sources. However, in the time period considered in this study, the market share of electric vehicles is negligible.



Note: Prepared by authors. Data from IEA (2018) and ODYSSEE (2018a)

4.1 The conditional convergence dynamic panel data model

We present next a conditional convergence dynamic panel data model for energy consumption in the road transport sector. In addition to analyse the determinants of energy consumption, we also want to characterize how the growth rates of the potential explanatory variables may also affect the convergence speed. We connect this latter analysis with the results illustrated in Table 3 and Figure 5 above (i.e., the increase of the convergence speed over time). To tackle these issues, we use the strategy followed by Plümper and Schneider (2009) and Schmitt and Starke (2011), and estimate a conditional convergence model including a set of explanatory variables together with interaction terms with the lagged level of energy consumption. More explicitly, the growth rate of per capita energy consumption in the road transport sector (C_{it}) is specified as:

$$\Delta\ln(C_{it}) = \alpha_i + \tau_t + \rho_1 \ln(C_{i,t-1}) + \rho_2 \ln(C_{i,t-1})\,\Delta\ln(Z_{it}) + \gamma'\ln(Z_{it}) + \varepsilon_{it}, \quad (9)$$

where α_i captures fixed factors of each country not considered in the model (e.g., local policies and geographical, institutional or social fixed conditions), τ_t is a common time effect capturing time-varying shocks but common to all countries (e.g., regulatory changes, movement in international oil prices, etc.), ε_{it} is an error term which is assumed to be i.i.d normally distributed and the vector Z_{it} includes potential determinants of energy consumption. Finally, it is worth mentioning that the term associated with the convergence speed is now equal to $\rho_1 + \rho_2\,\Delta\ln Z_{it}$, due to it depends on the growth rates of the variables included in Z_{it}.

In Z_{it}, we consider a set of determinants commonly used in fuel consumption models. In general, income and employment fluctuations, fuel prices and any other indicator providing information related to the usage of passenger cars and freight traffic are good candidates for explaining fuel demand (see, e.g., González and Marrero, 2012; Marrero et al. 2019; Romero-Jordan, 2014; Santos, 2013; Schipper, 2011 and Zervas, 2010). In compact notation, Z_{it} can be expressed as (see Table A1 in Appendix A for details on sources and variable description):

$$Z_{it} = \{GDP_{it}, FP_{it}, PC_{it}, FT_{it}\}. \quad (10)$$

The first driver, GDP_{it}, reflects the economic activity through per capita GDP. The second term, FP_{it}, denotes the average fuel price.[16] The third term PC_{it} is a proxy for passenger car usage intensity and it is defined as the total number of passenger cars relative to the GDP. Lastly, the term FT_{it} is the freight traffic ratio, defined as the traffic of goods per kilometre relative to the traffic of passengers per kilometre in the road transport sector. [17]

In our preferred specification of (9), we consider both the country and the time fixed effects, as already discussed in Section 3.1. Note that when we include simultaneously country and time fixed effects we are specifying a two-way fixed effect model. Not considering them in our estimations may result in seriously biased concerns when country and time heterogeneity exists (Hsiao, 1986).

The easiest way to estimate a panel data model like (9) is to ignore any unobserved country specific heterogeneity – i.e., set $\alpha_i = \alpha$ for all *i* - and then apply OLS to pooled data. However, this strategy may result in seriously biased – more concretely, downward-biased in absolute value estimates of the coefficient associated to the dynamic term (ρ_1 in (9)) when country heterogeneity exists (Hsiao, 1986). In our case, the reason is because the resulting error term ε_{it} is correlated with at least the variable $\ln(C_{i,t-1})$ (and also with the variables included in Z_{it}) in (9), hence the regression may lead to an endogeneity bias. The standard alternative is to use a country Fixed Effect (FE) estimator. However, this strategy does not guarantee unbiased estimations due to, as opposed to pooled-OLS, this alternative yields to upward-biased in the absolute value of ρ_1. Therefore, an instrumental variable (IV) approach must be used to overcome these bias problems.[18]

For the IV approach, in the absence of suitable external instruments (as it is common in this literature), we use the lag levels of the explanatory variables as internal instruments. Before obtaining the estimates, we conduct several widely used tests to check for the endogeneity of the regressors, and the degree of exogeneity and weakness of the instruments. Initially, we check whether the assumed endogenous explanatory variables can be treated as exogeneous. For this purpose, we use the difference-in-Sargan test, in which the null hypothesis is that the explanatory variables are exogeneous.[19]

To assess the validity of the instruments, that is, that the instruments are exogenous or uncorrelated with the error term, we use the overidentification Hansen J-test, in which the null

[16] To calculate this average, we take the average price of gasoline and diesel weighted by the total consumption of both fuels in the road transport sector.

[17] In previous analyses, we estimated other equations including alternative regressors. For example, from the ODYSSEE database (ODYSSEE, 2018a), we use the stock of trucks and light vehicles, the registration of new passenger cars, the annual distance travelled, the fuel efficiency of passenger cars and trucks and, from the ITF Transport Statistics database (https://www.oecd-ilibrary.org/transport/data/itf-transport-statistics_trsprt-data-en), the road density and the road infrastructure investment. However, after a systematic evaluation of alternative models (available upon request), our final model was designed to reduce multicollinearity, and to guarantee the correct signs grounded by the theory, while preserving a sample size as large as possible. Note also that there are other factors that can influence fuel consumption. For example, in some countries the poor quality of the road infrastructure might reduce the mobility of vehicles (Luo et al., 2017), causing that motor vehicles spend more time on the road at a lower speed and leading to an increase in exhaust emissions (Gately et al., 2017). However, we do not have well-structured information of this type of information, which difficult their inclusion in our regression analysis.

[18] IV models are estimated using the ivreg2 command in STATA (Baum et al., 2003). An alternative strategy is to use a first-difference or system GMM approach (Blundell and Bond, 1998). This approach is appropriate when the cross-section dimension is much larger than the time series dimension, which is not the case in our sample (22 countries and 24 years). Otherwise, the system GMM approach generates overfitting problems because of the excessive number of instruments used in any specification, which leads to un-consistent estimates (see, among others, the discussion in Roodman, 2009). For that reason, we disregard this approach in our analysis.

[19] The difference-in-Sargan test statistic (or C-statistic) is distributed as chi-squared with degrees of freedom equal to the number of regressors tested and specified using the "endog" option in the ivreg2 command in STATA (Baum et al., 2003).

hypothesis is the joint validity of all instruments. Finally, to analyse whether the instruments are not weak, that is, sufficiently correlated with the endogenous regressor, we use tools specifically designed for settings with multiple endogenous regressors. Firstly, we consider the chi-squared underidentification test of Sanderson-Windmeijer (SW hereafter). In this case, the null hypothesis assumes that the particular endogenous regressor is unidentified. The rejection of the null supports identification, but still the correlation with the endogenous regressor can be weak. Thus, to check the weakness of the instruments we use, secondly, the Sanderson-Windmeijer F statistic test (SWF hereafter). In this case, the null hypothesis assumes that the instruments are weak. As a rule of thumb, it is common to consider a threshold value of 10 based on the work of Staiger and Stock (1997). However, Sanderson and Windmeijer (2016) show that the F statistic can be assessed against the Stock and Yogo (2005) critical values, where weakness is defined in terms of size of the bias of the IV estimator relative to the OLS estimator. In our estimation results, we show the Stock and Yogo critical values that allows a maximal relative bias that ranges between 5% and 30%.

4.2 Data description

We present next a set of descriptive statistics (Table 4) and perform a preliminary analysis of the variables used in model (9). Figure 7 shows the trends of all variables over the period considered (taking 1990 as a base year). The right-hand side of Figure 7 distinguishes the variables that conform the passenger car usage intensity and freight traffic ratios.

Gathering information from both Table 4 and Figure 7, we can highlight some relevant aspects. Because of the close relation between CO_2 emissions and energy consumption, the energy consumption of the road transport sector presents exactly the same temporal behaviour as the road transport CO_2 emissions (recall from Figure 1 in Section 3), with a period of decline during the economic crisis. The price of fuel has increased 79% since 1990, very similar to the increase in GDP per capita (76%). The passenger car usage intensity ratio (number of passenger cars relative to the GDP) has fallen during the period. As we can see in the right-hand side of Figure 7, this is explained by the fact that, at the beginning of the period, the stock of passenger cars grew faster than the GDP, while at the end of the period both variables grow at similar rates. Finally, the freight traffic ratio (traffic of goods relative to the traffic of passengers) has increased over time. Again, in the right-hand side of the figure, we can see that the cause of this trend is because the share of the goods traffic relative to passenger traffic has progressively increased. It is worth noting the strong fall in goods traffic after the 2007 crisis.

A closer inspection of data shows that countries with the highest and lowest levels of road energy consumption in 1990 are, respectively, Switzerland (0.76 tonnes of carbon per capita) and Poland (0.16 tonnes per capita), which also matches with the highest and lowest levels of GDP per capita ($37685 and $8205, respectively). In 2014, the highest and lowest levels of energy consumption belong to Austria (0.92 tonnes per capita) and Hungary (0.37 tonnes per capita), with GDP per capita levels of $37685 and $8205, respectively. In general, all countries have experienced increases in energy consumption and GDP per capita, however, there are countries that have decoupled GDP per capita from energy consumption in the road transport sector. These countries are United Kingdom, Switzerland and Finland, with growth rates between 1990 and 2014 of -11%, -10% and -1%, respectively, in energy consumption, and 65%, 55% and 59%, respectively, in GDP per capita.[20]

[20] The decoupling experienced by these countries might be due to multiple factors. For example, some (or all) of these countries may have improved the quality and accessibility of rail and public transport and the multimodality in urban areas, replaced their vehicle fleet by more fuel-efficient vehicles or displaced their freight road traffic onto waterways, airways and railways. Despite its obvious interest, the examination of these particular factors is out of the scope of this paper and deserves further study.

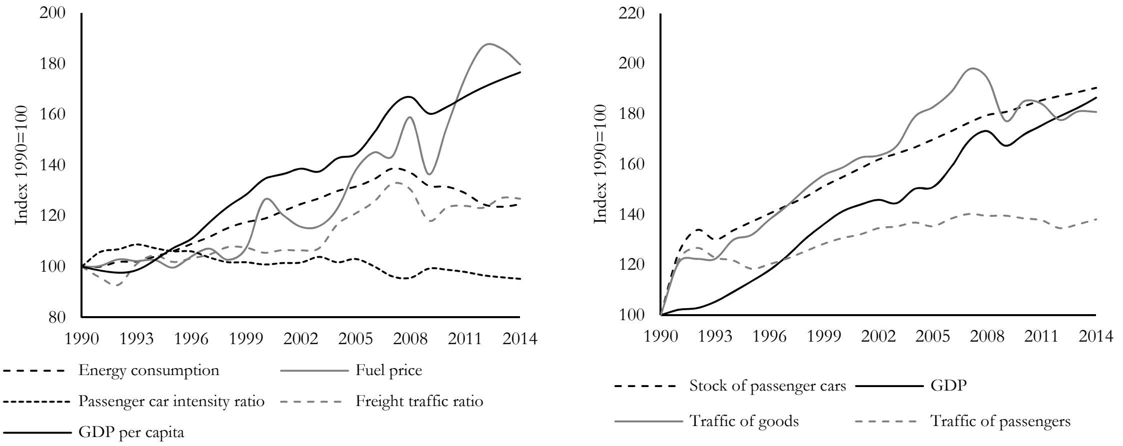
In terms of fuel prices, all countries follow a very similar trend, reflecting their strong dependence to international oil prices and the existence of a quite uniform fuel taxation policy across EU member states. In relation to the stock of passenger cars, all countries have increased their passenger car fleet, with growth rates between 1990 and 2014 higher than 100% in countries such as Portugal and Slovakia. However, in terms of intensity over GDP, some of them have been able to achieve a relative decoupling between stock of cars and GDP, especially at the end of the period (as shown in Figure 7). This is the case, for example, of Netherlands, with an increase of 103% between 1990 and 2014 in GDP ($392 billion to $796 billion) and an increase of 54% in the stock of passenger cars (5.2 to 8 million). Regarding passenger and goods traffic, the majority of countries have followed the same average behaviour shown in Figure 7, that is, upward trends in both variables but more pronounced in the case of goods traffic. Examples are Norway, with growth rates between 1990 and 2014 of 16% and 92% in passenger and goods traffic, respectively, or Belgium, with 7% and 60%, respectively.

Table 4. Descriptive statistics of energy consumption and driving factors

	1990				2014				Growth 1990-2014
	Mean	SD	Min	Max	Mean	SD	Min	Max	
Energy consumption of road transport per capita (tonnes per person)	0.49	0.18	0.16	0.76	0.61	0.16	0.37	0.92	24.60%
GDP per capita (chained PPPs in 2011US$)	21755	6699	8205	37685	38421	11519	21675	64274	76.61%
Fuel price (euros)	1.10	0.62	0.57	3.09	1.98	0.50	1.31	3.06	79.68%
Passenger car usage intensity ratio	13.39	2.72	5.69	18.28	12.74	3.43	7.72	20.59	-4.82%
Stock of passenger cars (million)	5.60	7.87	0.25	27.42	10.66	13.19	0.56	44.40	90.38%
GDP (chained PPPs in mil. 2011US$)	448747	582434	38409	2000000	836653	1017244	47106	3700000	86.44%
Freight traffic ratio	0.39	0.22	0.12	0.87	0.50	0.32	0.18	1.33	26.77%
Goods traffic (million goods per km)	47214	57550	2635	177945	85336	113798	9458	468900	80.74%
Passenger traffic (million passengers per km)	147969	192901	21845	599768	204273	263810	15258	939400	38.05%

Note: Prepared by authors. Data from IEA (2018), ODYSSEE (2018a) and Penn World Table 9.0 (Feenstra et al., 2015)

Figure 7. Trends of energy consumption and driving factors in the EU (Index 1990=100)



Note: Prepared by authors. Data from IEA (2018), ODYSSEE (2018a) and Penn World Table 9.0 (Feenstra et al., 2015)

Before showing the estimation results, we examine the potential multicollinearity problem between our driving factors. We present in Table 5 the Pearson correlation coefficient among explanatory variables, as well as the Variance Inflation Factor (VIF) test. In view of Table 5, the correlation coefficients never exceed 0.6 in absolute terms (that of GDP per capita and passenger car usage intensity ratio is -0.6), while the greater VIF value is 1.88. Our VIF values are smaller than the conventionally used critical values, which are 10 (Chaterjee and Price, 1977) and 5 (Urban and Mayerl, 2011). Hence, we can conclude that, in our sample, there are no serious concerns of collinearity among the driving factors of energy consumption in the road transport sector.[21]

Table 5. Correlation and Variance Inflation Factor (VIF) among driving factors

	GDP per capita (log)	Fuel price (log)	Passenger car usage intensity ratio (log)	Freight traffic ratio (log)	VIF
GDP per capita (log)	1				1.88
Fuel price (log)	-0.26	1			1.19
Passenger car usage intensity ratio (log)	-0.61	0.22	1		1.79
Freight traffic ratio (log)	-0.31	0.39	0.08	1	1.23

Note: Prepared by authors

4.3 Estimation results

We show next the estimation results of equation (9), under alternative specifications and using different econometric approaches. For illustrative purposes, we present the results in the following sequence. First, in Table 7, we estimate equation (9) not including the interaction terms and considering several assumptions in relation to the inclusion of country fixed effects and control variables. As in Section 3.2, we consider time fixed effects in all models. Second, we estimate different models incorporating the interaction terms in (9), using FE and IV methods. To avoid strong collinearity problems, we estimate the interaction terms one by one. Therefore, in each case, the parameter ρ_2 captures the effect on the convergence speed of the

[21] In a previous analysis, we excluded the variable "distance travelled by passenger cars" because its inclusion was causing collinearity problems in the model.

variations in the growth rate of each variable included in Z_{it}. The main results of this part are presented in Tables 8 and 10.

For the IV approach (models IV1, IV2, IV3) in Table 7, our baseline specification considers two lags of each right-hand side variables to instrument the corresponding endogenous regressors. Table A3 in Appendix A shows a robustness analysis of IV models using alternative lag-structures for the instrument set, using also one and three lags. The results show that the coefficients are robust to different lag selection, both in terms of magnitude and significance. We choose the two-lag structure as our baseline scenario for several reasons. With respect to the one-lag case, the inclusion of additional instruments can increase the precision of the estimates and allows to test the validity of the instruments using an over-identifying restriction (Hansen) test.[22] With respect to the three-lag case, the sample size is higher, we find a slightly better performance in terms of strength (the F-statistic of the SWF test are greater) and we reduce the potential over-fitting problem of using too-many instruments (Roodman, 2009), while no big differences in terms of validity of the instruments (Hansen J-test) are found.

Before showing the estimated results (Table 7), we test if the explanatory variables in (9) can be treated or not as exogeneous regressors in the IV approach. Table 6 shows the endogeneity test for each regressor. The results indicate that the null hypothesis of exogeneity is clearly not rejected in the case of the freight traffic ratio, thus we treat this variable as exogeneous. In the case of the fuel price, the p-value of the test is slightly higher than 0.10 but, to be conservative, in order to prevent the reverse causality between fuel prices and energy consumption, we opted to treat it as endogenous. For the lagged energy consumption term, per capita GDP and the passenger car usage intensity ratio, the null hypothesis of exogeneity is rejected, so they will be also instrumented.[23]

Several results can be highlighted from Table 7. First, note that, as expected, pooled-OLS estimations show convergence coefficients that are biased downward, while those given by the fixed-effects approach (FE1) tend to be biased upward. Our estimated coefficient using IV (IV1) is between those conventional estimates, thus confirming the right direction of our IV results.[24] Second, in models in which fixed effects are included, the speed of convergence increases. The change of the convergence speed ranges from 4.55% to 10.11% and from 4.57% to 11.88% when moving, respectively, from OLS to FE1, and from IV1 to IV2 estimates. Third, when the driving factors are also included in the model, the convergence speed increases rapidly, suggesting that these variables have an important role in conditioning the convergence process. Fourth, the sign and significance of the estimated coefficients are maintained using both FE and IV approaches. Lastly, in relation to model IV3, the SW and SWF tests indicate that underidentification and weakness, respectively, are not a concern in our specification. Likewise, the Hansen p-value greater than 0.10 indicates that the null hypothesis of joint validity of all instruments cannot be rejected at a 10% level of significance.

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[22] Note that models with one lag in Table A3 in Appendix A are exactly identified (same number of regressors and instruments) so overidentifying restrictions tests cannot be computed.

[23] We obtain the same results using alternative lag-structures (one or three lags) for the instrument set.

[24] A dynamic model can be expressed with the endogenous variable in level or in first difference (as in our case). In levels $\ln(y_{it}) = \alpha + \lambda \ln(y_{i,t-1})$ convergence exists when $\lambda < 1$. Pooled-OLS tends to be biased upwards (λ close to 1 and consequently lower speed of convergence) while FE tends to be biased downwards (higher speed of convergence). In first difference $\Delta\ln(y_{it}) = \alpha + \underbrace{(\lambda - 1)}_{\rho} \ln(y_{i,t-1})$ convergence exists when $\rho < 0$ ($\lambda < 1$). In this case, Pooled-OLS tends to be biased downwards because it generates estimations of ρ negative and close to 0 in absolute value. In both cases, OLS establish the lower bound in terms the convergence speed.

Table 6. Endogeneity test (difference-in-Sargan test)

Regressor	Statistic	Chi-sq (1) p-value
Lag of total energy consumption of road transport per capita (log)	3.81	0.05
GDP per capita (log)	8.57	0.00
Fuel price (log)	2.32	0.12
Passenger car usage intensity ratio (log)	2.56	0.10
Freight traffic ratio (log)	0.04	0.84

Note: Prepared by authors. H0: the regressor is exogenous. Rejection of H0 means that the regressor cannot be treated as exogenous and instruments are needed.

The descriptive statistics in Table 4 and Figure 7 can help us to understand the effect of the control variables on energy consumption (and hence on CO_2 emissions) in the road transport sector. GDP per capita, passenger car usage intensity and freight traffic ratios are positively correlated with the growth rate of energy consumption, whereas fuel price is negatively correlated. For example, taking into account (as a reference) the average levels of the variables in 2014 and models FE2 and IV3, the estimates indicate that a 10% increase in GDP per capita (i.e., moving from $38421 to $42263) is associated with an increase in energy consumption of about 1.6% - 1.7% (i.e., moving from 0.61 to 0.62 tonnes per person); an increase of 10% in fuel prices (from €1.98 to €2.18) is associated with a reduction of energy consumption of 0.8% - 1.1%. This last result indicates that fuel demand is highly inelastic, supporting the idea that fuel taxes are good for maximizing fiscal revenues but less good for reducing fuel consumption (Kirby et al., 2000). In the case of the ratios, 10% increase in the passenger car usage intensity entails an increase in energy consumption of 0.8% - 1.2%, while the same increase in the freight traffic increases the consumption by about 0.5 - 0.6%. In both cases, keeping the denominator constant, 10% increases entail the same increase in the stock of passenger cars and in goods traffic.

In the transport literature, a common result is that the income elasticities are greater than fuel price elasticities for energy (fuel) consumption in the transport sector (Goodwin et al., 2004). In terms of magnitudes, Goodwin et al. (2004)'s review of dynamic estimation studies establishes average values of 0.39 and -0.25 for income and price elasticities, respectively. Other reviews, such as the one conducted by Dahl and Sterner (1991), gives ranges of 0.30 to 0.52 for income and of -0.2 to -0.3 for price elasticities. Both studies mention the large standard deviations because of the numerous sources of variation in each particular study. In our case, the values are in the lower range of the literature, a fact that might be related with the specific sample, time period or geographical context chosen.

Tables 8 and 10 show, respectively, the FE and IV estimation results of the models that include the interaction terms (equation (9)). In these models, we always include country and time fixed effects. As in the IV models estimated in Table 7, we also check if the interaction terms can be treated as exogeneous. Following the results obtained with the difference-in-Sargan test (Table 9), we consider only the interaction with the growth rate of the GDP per capita as endogenous. The remaining cross terms are treated as exogenous.

Initially, to treat the endogeneity of the GDP interaction term, we use two lags of the variable as instrument, as in the case of the rest of endogenous regressors. However, by using this strategy, we have a weak identification problem, reflected by the small level of the SWF test for this particular regressor. Note also that the inclusion of two lags for the interaction term, together with the two lags for lagged energy and per capita GDP, might incur in important collinearity problems. As an alternative, we propose to be more parsimonious and use only one lag to instrument this interaction term.[25] Table A4 of Appendix A shows a robustness analysis of the IV models estimated in Table 10 in relation to different lag selection (one, two and three lags) for both the regressors and the interaction terms. Comparing columns (5) and (6) in Table A4, we observe that using one lag as instrument for the interaction with GDP per capita leads to a better performance in terms of strength (i.e., the F-stat of 5.06 of the SWF test now exceeds the threshold of 30% maximal relative bias), and of instruments validity (i.e., the p-value of the Hansen J-test is greater than the model considering two lags). Nevertheless, it is worth mentioning that the coefficients of the interaction and of the rest of the variables are robust to the choice between one, two or three lags to instrument the interaction term.

Table 7. A model of energy consumption in the road transport sector: pool-OLS, FE and IV estimates

Dependent variable: Annual growth rate of per capita energy consumption of road transport						
	OLS	**FE 1**	**FE 2**	**IV 1**	**IV 2**	**IV 3**
Constant	-0.00747	-0.0432***	-0.821**	-0.0277***	-0.0201*	-0.504
	(-0.82)	(-4.03)	(-2.63)	(-3.27)	(-1.68)	(-1.52)
Lag of total energy consumption of road transport per capita (log)	-0.0445***	-0.0962***	-0.234***	-0.0447***	-0.112***	-0.284***
	(-7.34)	(-6.72)	(-10.52)	(-7.58)	(-6.64)	(-7.99)
GDP per capita (log)			0.166***			0.173***
			(-5.62)			(-3.91)
Fuel price (log)			-0.0858***			-0.115***
			(-4.63)			(-3.87)
Passenger car usage intensity ratio (log)			0.0825***			0.118***
			(-5.46)			(-3.48)
Freight traffic ratio (log)			0.0522***			0.0655***
			(-5.16)			(-5.16)
Convergence speed	4.55%	10.11%	26.66%	4.57%	11.88%	33.41%
Half-life (years)	15.57	7.19	2.93	15.50	6.18	2.40
Country Fixed Effects	No	Yes	Yes	No	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	447	447	447	420	420	406
adj. R-sq	0.366	0.388	0.492	0.364	0.455	0.566
Underidentification test (SW Chi-squared) (p-values in brackets)						
Lag of total energy consumption of road transport per capita (log)				12212 (0.00)	2289 (0.00)	442.44 (0.00)
GDP per capita (log)						607.40 (0.00)
Fuel price (log)						393.23 (0.00)
Passenger car usage intensity ratio (log)						515.86 (0.00)
Weak identification test (SW F)						
Lag of total energy consumption of road transport per capita (log)				5757.53	1021.90	77.15
GDP per capita (log)						105.92
Fuel price (log)						68.57

[25] An alternative strategy is to instrument only the part of the interaction affected by the endogeneity problem as, for example, in Brüeckner and Lederman (2018). We tried several structures to check whether the source of endogeneity was due to the lag of energy consumption or, instead, to the growth rate of the GDP per capita, and concluded that both variables were affected by endogeneity. Accordingly, we adopted our strategy of instrumenting both parts of the interaction.

Passenger car usage intensity ratio (log)			89.96
Stock and yogo critical values			
5% max relative bias	--	--	20.25
10% max relative bias	--	--	11.39
20% max relative bias	--	--	6.69
30% max relative bias	--	--	4.99
Overidentification test			
Hansen J stat	0.553	0.00969	4.281
Hansen p-value	0.457	0.922	0.369

*Note: Prepared by authors. t-statistics in parentheses. * p<0.10 *** p<0.0.05 *** p<0.01.*
In the IV models, the instruments for the endogenous explanatory variables are the first and second lag of each variable

Table 8. A model of energy consumption in the road transport sector: FE estimates with interaction terms

Dependent variable: Annual growth rate of per capita energy consumption of road transport				
Constant	-0.532 (-1.67)	-0.812** (-2.66)	-0.749** (-2.47)	-0.903** (-2.78)
Lag of total energy consumption of road transport per capita (log)	-0.209*** (-8.86)	-0.247*** (-9.05)	-0.238*** (-10.76)	-0.238*** (-10.44)
GDP per capita (log)	0.147*** (-5.17)	0.176*** (-5.38)	0.165*** (-5.4)	0.180*** (-5.95)
Fuel price (log)	-0.0848*** (-4.45)	-0.102*** (-6.44)	-0.0878*** (-4.97)	-0.0733*** (-4.01)
Passenger car usage intensity ratio (log)	0.0917*** (-4.99)	0.0934*** (-4.94)	0.0880*** (-5.86)	0.0887*** (-4.46)
Freight traffic ratio (log)	0.0454*** (-4.02)	0.0526*** (-4.73)	0.0553*** (-5.56)	0.0494*** (-5.02)
Interactions with the lag of road transport CO2 emissions per capita				
GDP per capita (growth rate)	-0.450*** (-4.85)			
Fuel price (growth rate)		0.143** (-2.12)		
Passenger car usage intensity ratio (growth rate)			0.119* (-2.02)	
Freight traffic ratio (growth rate)				-0.0296 (-0.77)
Country Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
N	447	435	446	443
adj. R-sq	0.544	0.542	0.497	0.515

*Note: Prepared by authors. t-statistics in parentheses. * p<0.10 *** p<0.0.05 *** p<0.01*

Table 9. Endogeneity test of interaction terms (difference-in-Sargan test)

Regressor	Statistic	Chi-sq (1) p-value
GDP per capita (growth rate)	4.85	0.02
Fuel price (growth rate)	0.29	0.58
Passenger car usage intensity ratio (growth rate)	1.18	0.27
Freight traffic ratio (growth rate)	0.01	0.92

Note: Prepared by authors. H0: the regressor is exogenous. Rejection of H0 means that the regressor cannot be treated as exogenous and instruments are needed

In view of tables 8 and 10, it is worth noting that the sign of the coefficients is robust to the estimation method (FE versus IV). Further, the coefficients associated with the driving factors maintain the same sign and similar magnitude to those estimated in Table 7. Looking at the tables separately, and reading the estimation results from left to right, we see can that the coefficients are robust to the introduction of the different interaction terms, revealing that with this strategy the estimations do not present serious problems of collinearity. For instance, the fuel price coefficient ranges from -0.07 to -0.10 in FE models and from -0.09 to -0.12 in IV models.

However, the most interesting results are those for the interaction terms. In both estimation approaches, the interaction terms of per capita GDP, fuel price and passenger car usage intensity ratio are significant. The other interaction term (freight traffic ratio) is not significant, implying that in our models it is not correlated with changes in the speed of convergence. The main difference between the estimation approaches is that the coefficients of the interaction terms are appreciably higher in the IV results. The SW, SWF and Hansen J-test indicate that our IV models do not suffer major problems of under-identification, weak identification and overidentification, respectively, so, due to the superior performance of the IV estimation, we choose Table 10 to finish the presentation of the results and to plot Figures 8, 9 and 10.

Figures 8, 9 and 10 show the effect of each significant interaction term in the IV models. The solid sloping line in the figures indicates how much the ρ parameter changes with the growth rate of each of the variables under consideration. Accordingly, it is easy to see that 0 growth rates on the x-axis correspond to the coefficient associated with the lag parameter (-0.25, -0.28 and -0.29 in Figures 7, 8 and 9, respectively). The 95% confidence intervals plotted in dotted lines allow us to determine the conditions under which specific growth rate has a statistically significant effect whenever both the upper and lower bounds of the interval are above (below) the zero line. In the figures, we also plot the average growth rate and standard deviation of the variable corresponding to the last five years (2009-2014) in order to facilitate the understanding of the potential variation of each factor.

Regarding the GDP per capita, we can see that the growth rate of this variable is positively correlated with the convergence speed. The figure 8 tell us, for example, that an increase in GDP per capita of 12% (the average growth rate for the last five years in our set of EU countries) would be related with an increase in the convergence speed from 29%, or a half-life of 2.7 years ($\rho = -0.253$), to 43%, or a half-life of 1.9 years ($\rho = -0.253 - 0.796 * 0.12$). In Figure 9, we can see, on the contrary, that the growth rate of the fuel price is negatively correlated with the convergence speed. In this case, for example, an increase in the fuel price of 31% (average growth rate between 2009 and 2014) is related with a decrease in the convergence speed from 33%, or a half-life of 2.4 years ($\rho = -0.281$), to 25%, or a half-life of 3 years ($\rho = -0.281 + 0.181 * 0.31$). Finally, like fuel price, the passenger car usage intensity ratio is also negatively correlated with the convergence speed. In this respect, reductions in the stock of passenger cars (keeping GDP constant) or increases in the GDP (keeping the stock of cars constant) are associated with a higher convergence speed. Lastly, note that freight traffic relative to passenger traffic is relevant in explaining the evolution of the road transport energy consumption, but it does not have a significant effect on the speed of convergence.

Thus, if we connect these results with those results shown in Table 3 and Figure 5 in section 3.2, the evolution of GDP per capita, fuel prices and passenger car usage intensity between 1990 and 2014 might help to explain the increase in the convergence speed of CO_2 emissions in the road transport sector in Europe. Moreover, we can also infer that a change in these factors would have a double impact on the evolution of CO_2 emissions in the road transport sector: they would affect the growth of CO_2 emissions (channelled through energy consumption), but also the convergence speed towards the respective long-run equilibrium trajectory of each country.

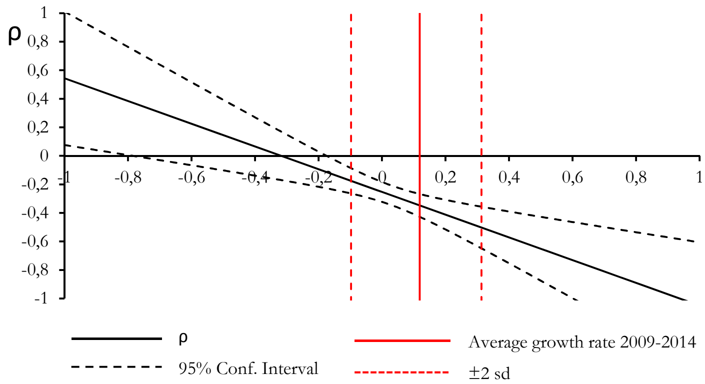
Table 10. A model of energy consumption in the road transport sector: IV estimates with interaction terms

Dependent variable: Annual growth rate of per capita energy consumption of road transport				
Constant	-1.083***	-0.586**	-0.651**	-0.745**
	(-3.08)	(-1.98)	(-2.20)	(-2.43)
Lag of total energy consumption of road transport per capita (log)	-0.253***	-0.281***	-0.291***	-0.273***
	(-7.12)	(-9.20)	(-8.34)	(-7.59)
GDP per capita (log)	0.220***	0.174***	0.184***	0.184***
	-(4.72)	-(4.61)	-(4.35)	-(4.12)
Fuel price (log)	-0.09***	-0.123***	-0.12***	-0.09***
	(-2.98)	(-4.92)	(-4.11)	(-3.14)
Passenger car usage intensity ratio (log)	0.110***	0.112***	0.115***	0.106***
	-(3.46)	-(4.03)	-(3.41)	-(3.04)
Freight traffic ratio (log)	0.0399***	0.0591***	0.0643***	0.0557***
	-(3.16)	-(5.67)	-(5.17)	-(4.48)
Interactions with the lag of road transport CO_2 emissions per capita				
GDP per capita (growth rate)	-0.796***			
	(-3.47)			
Fuel price (growth rate)		0.181***		
		-(4.26)		
Passenger car usage intensity ratio (growth rate)			0.146*	
			-(1.83)	
Freight traffic ratio (growth rate)				-0.0232
				(-0.77)
Country Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
N	406	402	406	403
adj. R-sq	0.562	0.617	0.572	0.601
Underidentification test (SW Chi-squared) (p-values in brackets)				
Lag of total energy consumption of road transport per capita (log)	352.67 (0.00)	494.22 (0.00)	443.34 (0.00)	407.42 (0.00)
GDP per capita (log)	257.38 (0.00)	655.57 (0.00)	704.2 (0.00)	552.99 (0.00)
Fuel price (log)	292.45 (0.00)	853.83 (0.00)	346.28 (0.00)	355.86 (0.00)

Passenger car usage intensity ratio (log)	484.82 (0.00)	789.32 (0.00)	507.84 (0.00)	452.62 (0.00)
GDP per capita (growth rate)	29.1 (0.00)			
Weak identification test (SW F)				
Lag of total energy consumption of road transport per capita (log)	61.33	85.81	77.09	70.77
GDP per capita (log)	44.76	113.83	122.46	96.05
Fuel price (log)	50.85	148.25	60.22	61.81
Passenger car usage intensity ratio (log)	84.31	137.05	88.31	78.62
GDP per capita (growth rate)	5.06			
Stock and yogo critical values				
5% max relative bias	20.53	20.25	20.25	20.25
10% max relative bias	11.46	11.39	11.39	11.39
20% max relative bias	6.65	6.69	6.69	6.69
30% max relative bias	4.92	4.99	4.99	4.99
Overidentification test				
Hansen J stat	2.777	6.153	3.423	6.676
Hansen p-value	0.596	0.188	0.49	0.154

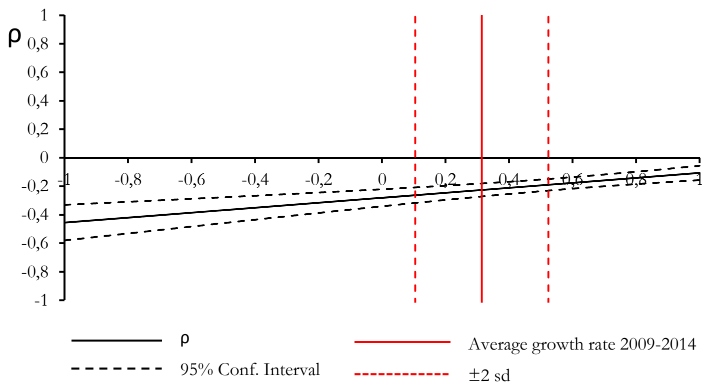
*Note: Prepared by authors. t-statistics in parentheses. * p<0.10 *** p<0.0.05 *** p<0.01*
The instruments for the endogenous explanatory variables are the first and second lags of each variable, except for the interaction with the growth rate of the GDP per capita, which only one lag is taken

Figure 8. Effect of the growth rate of GDP per capita on the convergence speed



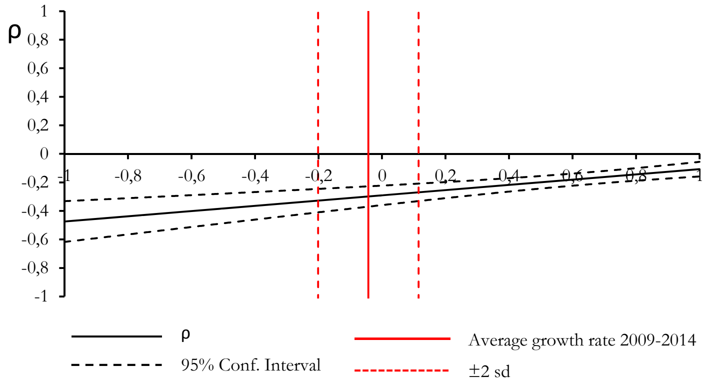
Note: Prepared by authors

Figure 9. Effect of the growth rate of fuel price on the convergence speed



te: Prepared by authors

Figure 10. Effect of the growth rate of passenger car usage intensity ratio on the convergence speed



Note: Prepared by authors

6. Conclusions

Using a panel data of 22 European Union countries and a time period from 1990 to 2014, we examined the concepts of β (absolute and conditional), σ and club convergence in relation to road transport CO_2 emissions per capita. Using different methodologies, we found strong evidence of reductions in the disparities in road transport CO_2 emission levels and of a conditional β-convergence process. Thus, countries with lower (higher) initial levels of emissions are increasing (reducing) emissions faster but conditional on certain structural factors. Further, we presented evidence that the conditional convergence process has accelerated during the considered period. A plausible reason for finding conditional convergence instead of club convergence is that the countries of our sample share the same growth dynamics, which can be explained by the homogeneity of the sample (developed countries from the EU). By contrast, for the club convergence case, each club has its own growth dynamics determined by initial conditions, a result which is more likely to be found in more heterogeneous samples (e.g., among OECD countries).

Due to the close relationship between CO_2 emissions and energy (fuel) consumption in the road transport sector for our sample, our strategy to explain the dynamics of road transport CO_2 emissions was to estimate a conditional convergence dynamic panel data model on energy consumption. Our results provide evidence that per capita GDP, passenger car usage intensity (proxy by passenger cars relative to GDP) and relative freight traffic (traffic of goods relative to traffic of passengers) are positively correlated with the growth rate of energy consumption in the road transport sector, whereas fuel price is negatively correlated. Additionally, the growth rates of GDP, fuel price and passenger car usage intensity also appear to have a significant effect on the speed of convergence. These results are robust to alternative model specifications and econometric methods.

Directly linked with policy goals and objectives, our analysis has shown that, despite the evidence of reduction in disparities, the convergence process in road transport CO_2 emission in Europe is strongly conditioned by certain factors, implying that the laggard countries may never catch up with the leaders unless there is an equality in these structural factors. Further, the convergence process may accelerate or decelerate depending on variables closely linked to economic activity, such as GDP growth and fuel prices changes. In this regard, the growing concern about climate change may lead to the implementation of emission abatement policies associated with higher costs that may negatively affect the convergence between EU countries. This avenue of research can be extended in several directions: first, by estimating models that consider the role of the spatial interrelationships between the economies; second, by studying the long-term steady state levels of emissions towards which countries are moving; and finally, by analysing the relationship between transport sector emissions and economic growth.

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APPENDIX A

Table A1. Variables description

Variable	Source codification	Source
Total CO_2 emissions from Fuel Combustion (Mt of CO_2)	CO2FCOMB	International Energy Agency (IEA) CO_2 emissions from fuel combustion
Transport CO_2 emissions (Mt of CO_2)	TOTTRANS	
Road transport CO_2 Emissions (Mt of CO_2)	ROAD	
Total energy consumption of road transport (Mtoe)	toccfrou	ODYSSEE - Energy Database
Stock of passenger cars (million)	nbrvpc	
Road goods traffic (goods per kilometre)	tkmrou	
Road passenger traffic (passengers per kilometre)	pkmrou	
Weighted average fuel price (euros)	Regular, Mid, High Gasoline. Diesel	International Energy Agency (IEA) - World Energy Prices Database
GDP (chained PPPs in mil. 2011US$)	rgdpe	Penn World Table 9.0
Population (million)	pop	Penn World Table 9.0

Note: Prepared by authors

Table A2. Homogenous vs heterogeneous autoregressive coefficients

Dependent variable: Annual growth rate of road CO2 emissions per capita				
	Homogenous model		**Heterogeneous model**	
Constant	.0239***	(-6.4779)	.0259***	(-5.0816)
Lag of road CO2 emissions per capita (log)	-.0301***	(-5.1266)		
Lag of road CO2 emissions per capita (log) (by country)				
Austria			-0.0154	(-1.0834)
Belgium			-.0281*	(-1.8712)
Croatia			-0.0292	(-.8837)
Denmark			-.0349**	(-2.1006)
Finland			-.0435***	(-2.6929)
France			-.0419**	(-2.3091)
Germany			-.0419**	(-2.2446)
Greece			-.0666**	(-2.1998)
Hungary			-0.0134	(-.3213)
Ireland			-0.0143	(-.9808)
Italy			-.0418**	(-2.0982)
Latvia			-0.0225	(-.5739)
Netherlands			-.0399**	(-2.1555)
Norway			-.0305*	(-1.7968)
Poland			-0.0449	(-1.5912)
Portugal			-0.0455	(-1.632)
Slovakia			-0.0313	(-.744)
Slovenia			-0.0104	(-.6349)
Spain			-.0372*	(-1.8637)
Sweden			-.0356**	(-2.3122)
Switzerland			-.0368**	(-2.3015)
United Kingdom			-.0468**	(-2.4799)
N	528		528	
adj. R-sq	0.0458		0.0262	
F-test (Null hypothesis: autoregressive coefficients are homogenous)				
F-stat		0.50		
p-value		0.97		

*Note: Prepared by authors. t-statistics in parentheses. * p<0.10 *** p<0.0.05 *** p<0.01*

Table A3. Robustness analysis to different lag selection in IV models

Dependent variable: Annual growth rate of total energy consumption of road transport per capita									
Number of lags	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
Constant	0.0026	-0.027***	-0.0103	0.00614	-0.0201*	-0.00628	-0.358	-0.504	-0.465
	(-0.38)	(-3.27)	(-1.54)	-0.52	(-1.68)	(-0.54)	(-1.21)	(-1.52)	(-1.29)
Lag of total energy consumption of road transport per capita (log)	-0.045***	-0.045***	-0.044***	-0.110***	-0.112***	-0.117***	-0.267***	-0.284***	-0.290***
	(-7.81)	(-7.58)	(-7.36)	(-6.89)	(-6.64)	(-6.76)	(-7.91)	(-7.99)	(-8.02)
GDP per capita (log)							0.162***	0.173***	0.175***
							-3.9	-3.91	-3.84
Fuel price (log)							-0.0971***	-0.115***	-0.112***
							(-3.68)	(-3.87)	(-3.49)
Passenger car usage intensity ratio (log)							0.119***	0.118***	0.123***
							-3.7	-3.48	-3.44
Freight traffic ratio (log)							0.0670***	0.0655***	0.0661***
							-5.42	-5.16	-5.15
Country fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	434	420	405	434	420	405	426	406	393
adj. R-sq	0.368	0.364	0.367	0.455	0.455	0.467	0.554	0.566	0.578
Underidentification test (SW Chi-squared) (p-values in brackets)									
Lag of total energy consumption of road transport per capita (log)	12321	12212	14809	2490	2289	2197	461.40	442.44	447.20
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GDP per capita (log)							694.44	607.40	618.06
							(0.00)	(0.00)	(0.00)
Fuel price (log)							384.44	393.23	375.70
							(0.00)	(0.00)	(0.00)
Passenger car usage intensity ratio (log)							511.04	515.86	482.59
							(0.00)	(0.00)	(0.00)
Weak identification test (SW F)									
Lag of total energy consumption of road transport per capita (log)	11640.00	5757.00	4643.00	2232.00	1021.00	651.00	408.33	77.15	64.67
GDP per capita (log)							614.57	105.92	89.38
Fuel price (log)							340.23	68.57	54.33
Passenger car usage intensity ratio (log)							452.26	89.96	69.79
Stock and yogo critical values									
5% max relative bias	--	--	--	--	--	--	16.85	20.25	20.53
10% max relative bias	--	--	--	--	--	--	10.27	11.39	11.46
20% max relative bias	--	--	--	--	--	--	6.71	6.69	6.65
30% max relative bias	--	--	--	--	--	--	5.34	4.99	4.92
Overidentification test									
Hansen J stat	--	0.553	0.955	--	0.00969	0.305	--	4.281	5.146
Hansen p-value	--	0.457	0.62	--	0.922	0.858	--	0.369	0.398

*Note: Prepared by authors. t-statistics in parentheses. * p<0.10 *** p<0.0.05 *** p<0.01*

Table A4. Robustness analysis to different lag selection in IV models with interaction terms

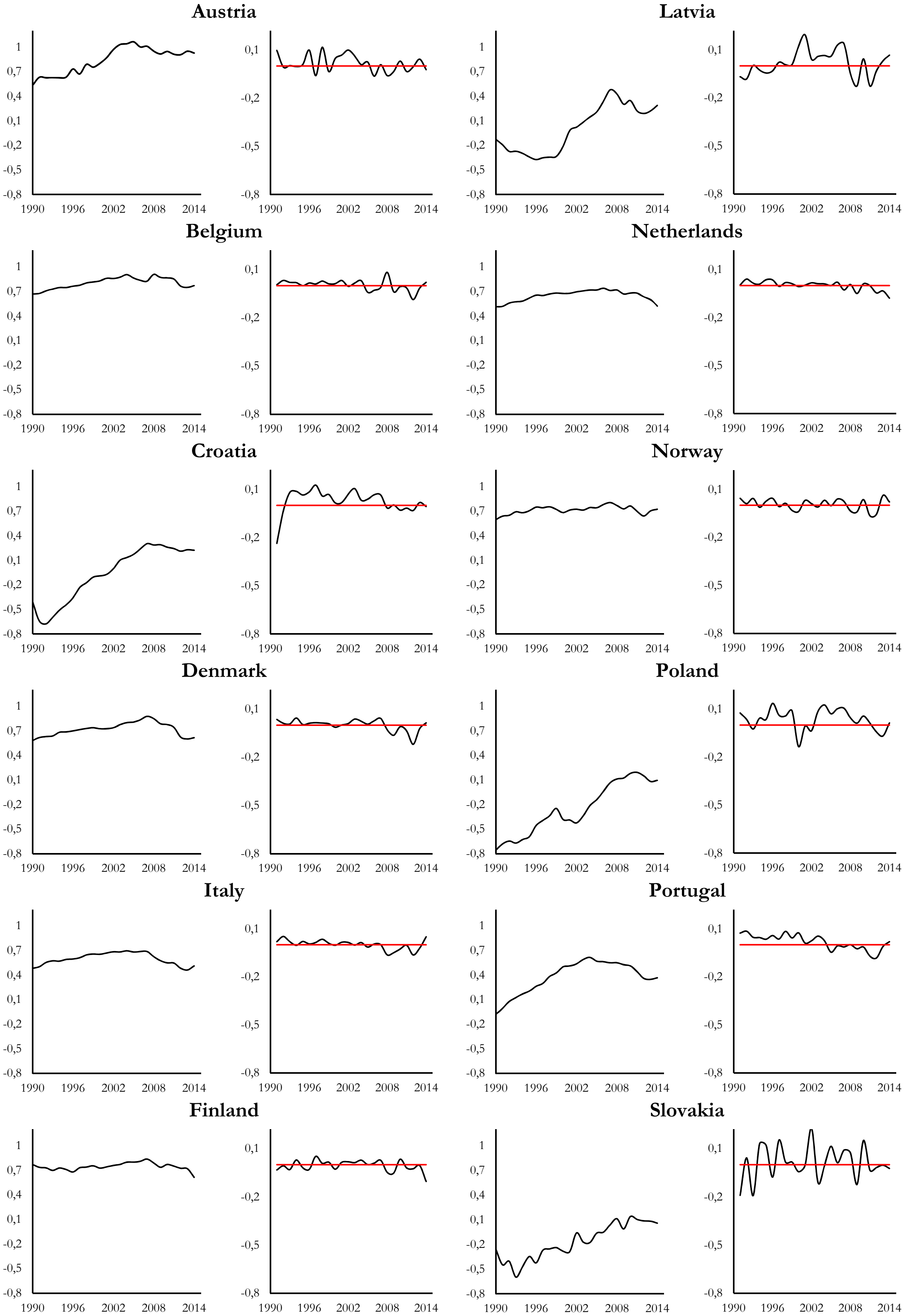
Dependent variable: Annual growth rate of total energy consumption of road transport per capita

Number of lags	1				2					3				
						a					a			
Constant	-0.998***	-0.418	-0.492*	-0.535*	-1.089***	-1.083***	-0.586**	-0.651**	-0.745**	-1.085***	-1.07***	-0.596*	-0.592*	-0.757**
	(-3.01)	(-1.53)	(-1.79)	(-1.92)	(-3.10)	(-3.08)	(-1.98)	(-2.20)	(-2.43)	(-2.91)	(-2.89)	(-1.94)	(-1.85)	(-2.36)
Lag of total energy consumption of road transport per capita (log)	-0.221***	-0.264***	-0.273***	-0.258***	-0.256***	-0.253***	-0.281***	-0.291***	-0.273***	-0.257***	-0.25***	-0.297***	-0.295***	-0.277***
	(-6.28)	(-8.90)	(-8.16)	(-7.64)	(-7.26)	(-7.12)	(-9.20)	(-8.34)	(-7.59)	(-7.04)	(-6.91)	(-9.71)	(-8.26)	(-7.36)
GDP per capita (log)	0.199***	0.169***	0.172***	0.171***	0.223***	0.220***	0.174***	0.184***	0.184***	0.231***	0.23***	0.188***	0.185***	0.188***
	-(4.43)	-(4.44)	-(4.25)	-(4.10)	-(4.81)	-(4.72)	-(4.61)	-(4.35)	-(4.12)	-(4.84)	-(4.63)	-(4.90)	-(4.23)	-(4.00)
Fuel price (log)	-0.082***	-0.098***	-0.100***	-0.075***	-0.091***	-0.090***	-0.123***	-0.119***	-0.088***	-0.088***	-0.08***	-0.123***	-0.117***	-0.082***
	(-2.92)	(-4.20)	(-3.86)	(-3.04)	(-2.99)	(-2.98)	(-4.92)	(-4.11)	(-3.14)	(-2.73)	(-2.72)	(-4.74)	(-3.73)	(-2.76)
Passenger car usage intensity ratio (log)	0.0955***	0.120***	0.117***	0.111***	0.112***	0.110***	0.112***	0.115***	0.106***	0.120***	0.116***	0.124***	0.121***	0.108***
	-(3.24)	-(4.15)	-(3.63)	-(3.39)	-(3.53)	-(3.46)	-(4.03)	-(3.41)	-(3.04)	-(3.69)	-(3.53)	-(4.51)	-(3.44)	-(2.89)
Freight traffic ratio (log)	0.0333***	0.0639***	0.0666***	0.0595***	0.0405***	0.0399***	0.0591***	0.0643***	0.0557***	0.0374***	0.037***	0.0601***	0.0643***	0.0554***
	-(2.70)	-(5.69)	-(5.45)	-(4.94)	-(3.19)	-(3.16)	-(5.67)	-(5.17)	-(4.48)	-(2.80)	-(2.78)	-(5.70)	-(5.15)	-(4.37)
Interactions with the lag of road transport CO2 emissions per capita														
GDP per capita (growth rate)	-0.976***				-0.804***	-0.796***				-0.836***	-0.813***			
	(-3.78)				(-3.49)	(-3.47)				(-3.75)	(-3.58)			
Fuel price (growth rate)		0.147***					0.181***					0.188***		
		-(2.98)					-(4.26)					-(4.46)		
Passenger car usage intensity ratio (growth rate)			0.116					0.146*					0.143*	
			-(1.53)					-(1.83)					-(1.70)	
Freight traffic ratio (growth rate)				-0.0217					-0.0232					-0.0222
				(-0.73)					(-0.77)					(-0.70)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	426	422	426	423	406	406	402	406	403	393	393	389	393	390
adj. R-sq	0.532	0.593	0.558	0.586	0.56	0.562	0.617	0.572	0.601	0.566	0.571	0.633	0.584	0.614
Underidentification test (SW Chi-squared) (p-values in brackets)														
Lag of total energy consumption of road transport per capita (log)	281.59	523.77	455.56	445.93	349.53	352.67	494.22	443.34	407.42	322.45	330.39	497.52	441.25	367.45
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GDP per capita (log)	200.48	757.01	721.82	662.96	261.72	257.38	655.57	704.2	552.99	282.26	249.60	650.87	682.83	509.43
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fuel price (log)	301.23	1013.18	340.56	369.82	294.57	292.45	853.83	346.28	355.86	292.47	285.66	809.91	336.82	327.63
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Passenger car usage intensity ratio (log)	487.84	775.54	516.65	477.64	491.61	484.82	789.32	507.84	452.62	433.38	417.84	713.4	490.35	376.5
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GDP per capita (growth rate)	24.32				29.49	29.1				31.18	30.08			
	(0.00)				(0.00)	(0.00)				(0.00)	(0.00)			
Weak identification test (SW F)														
Lag of total energy consumption of road transport per capita (log)	248.54	461.71	402.09	393.22	50.51	61.33	85.81	77.09	70.77	34.67	47.64	71.62	63.62	52.92
GDP per capita (log)	176.95	667.32	637.10	584.60	37.82	44.76	113.83	122.46	96.05	30.34	35.99	93.70	98.46	73.37
Fuel price (log)	265.87	893.14	300.59	326.11	42.57	50.85	148.25	60.22	61.81	31.44	41.19	116.59	48.57	47.19
Passenger car usage intensity ratio (log)	430.58	683.65	456.01	421.18	71.04	84.31	137.05	88.31	78.62	46.59	60.25	102.70	70.70	54.22
GDP per capita (growth rate)	21.46				4.26	5.06				3.35	4.34			
Stock and yogo critical values														
5% max relative bias	18.37	16.85	16.85	16.85	20.74	20.53	20.25	20.25	20.25	21.01	20.74	20.53	20.53	20.53
10% max relative bias	10.83	10.27	10.27	10.27	11.49	11.46	11.39	11.39	11.39	11.52	11.49	11.46	11.46	11.46
20% max relative bias	6.77	6.71	6.71	6.71	6.61	6.65	6.69	6.69	6.69	6.53	6.61	6.65	6.65	6.65
30% max relative bias	5.25	5.34	5.34	5.34	4.86	4.92	4.99	4.99	4.99	4.75	4.86	4.92	4.92	4.92
Overidentification test														
Hansen J stat	--	--	--	--	4.81	2.777	6.153	3.423	6.676	9.431	4.451	8.495	4.396	7.083
Hansen p-value	--	--	--	--	0.44	0.596	0.188	0.49	0.154	0.223	0.486	0.131	0.494	0.215

*Note: Prepared by authors. t-statistics in parentheses. * p<0.10 *** p<0.0.05 *** p<0.01*
a: Models considering only 1 lag for the interaction with the growth rate of GDP per capita

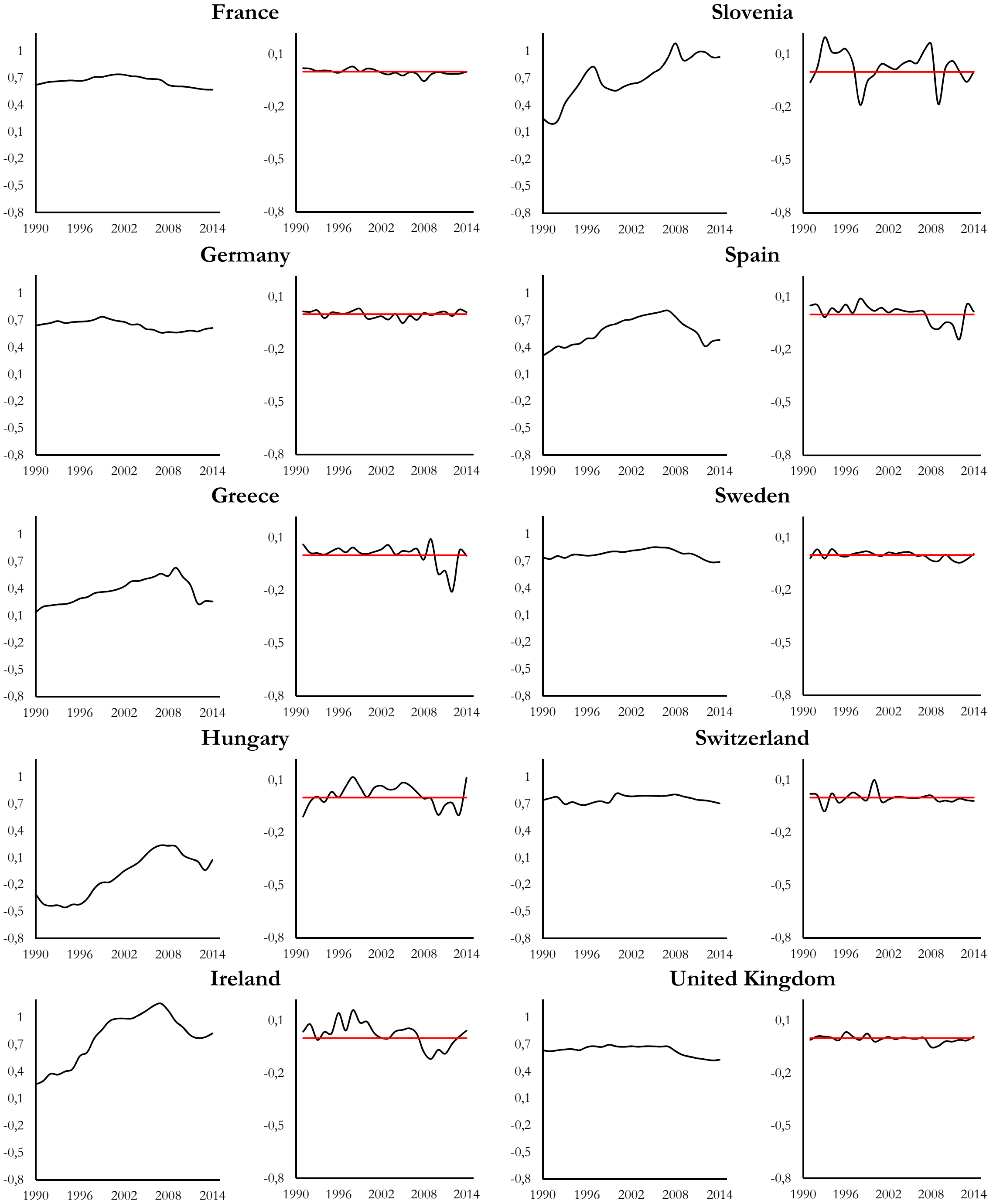
APPENDIX B

Figure B1. Log of road CO_2 emissions per capita. Level and first difference.



Note: For each country, the figure in the left show the log of the road CO_2 emissions per capita and, in the right, its growth rate

Figure B1. (continued)



Note: For each country, the figure in the left show the log of the road CO_2 emissions per capita and, in the right, its growth rate