INVESTIGATING PATTERNS OF CARBON CONVERGENCE IN AN UNEVEN ECONOMY: THE CASE OF TURKEY

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ABSTRACT

Turkey is known to suffer from severe volatility in its growth patterns, as well as from the uneven sectorial growth and employment. Volatile rates of emissions of gaseous pollutants across sectors are further manifestations of this uneven structure. The purpose of this study is two-fold: first, we check for dynamic patterns of convergence of carbon dioxide (CO_2) emissions across sectors; and second, using evidence from panel data econometrics, we search for the determinants of these processes utilizing macroeconomic explanatory variables. We find that based on various alternate criteria, CO_2 emissions and emission intensities measured as the share of CO_2 emissions per unit of value added display conditional convergence mainly driven by the business cycle. Furthermore, across sectors, the high technology activities display convergence over time; and yet, the medium technology sectors constituting the bulk of the aggregate value added display either poorly convergent or divergent trends. These results reveal that much of the emissions convergence is driven by the business cycle rather than the workings of discretionary mitigation policy.

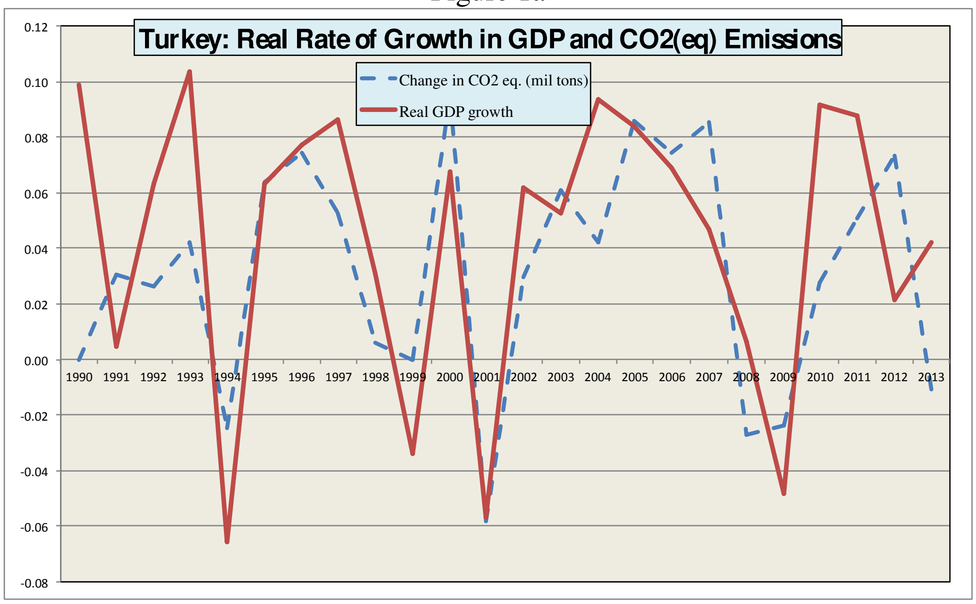
1. Motivation

Turkey's economy is known to display wide swings in its patterns of growth both in aggregate and also in its sectorial composition. The stop-and-go patterns of output growth are manifested not only in terms of mini-business cycles of economic activity, but also in terms of gaseous emissions across sectors. As of 2013, Turkey's total emissions of gaseous pollutants (in terms of carbon dioxide equivalent (CO_2 eq.) is estimated to be 459 million tons (mtons). About three quarters of this is reported to arise from energy-related activities, while 72 mtons are attributed to industrial processes. According to data from the International Energy Agency, with total emissions of 6.1 tons of CO_2 eq. per capita and 0.26 kg per $GDP, Turkey displays a lower figure in emissions in both accounts in comparison to the world and OECD averages. However, Turkey is also known to display one of the highest rates of growth in CO_2 eq. emissions among the emerging market economies. Turkey's CO_2 eq. emissions increased from 218 million tons in 1990, to 459 million tons in 2013; and is expected to increase to 822 million tons by 2030 (Acar and Yeldan, 2016). This suggests that Turkey will be on a divergent trend against many of the emerging market developing economies as well as the world averages over the next decades.

These assessments are succinctly narrated in Figures 1a and 1b below, where we display the rate of change in aggregate CO_2 eq. emissions against changes in real GDP over the post-1990 era. The close association between the real rate of change in CO_2 emissions and the real business cycles over this period is clearly visible for Turkey, suggesting that the much desired *decoupling* of gaseous emissions from real economic activity has not yet taken place. This observation further reveals the low elasticity of gaseous emissions in response to real growth, and that the returns to abatement policies had rather been dismal. This observation contrasts with the Asian emerging economies, where a substantial decoupling of gaseous emissions from real GDP growth is observable. (See Figures 1a and 1b).

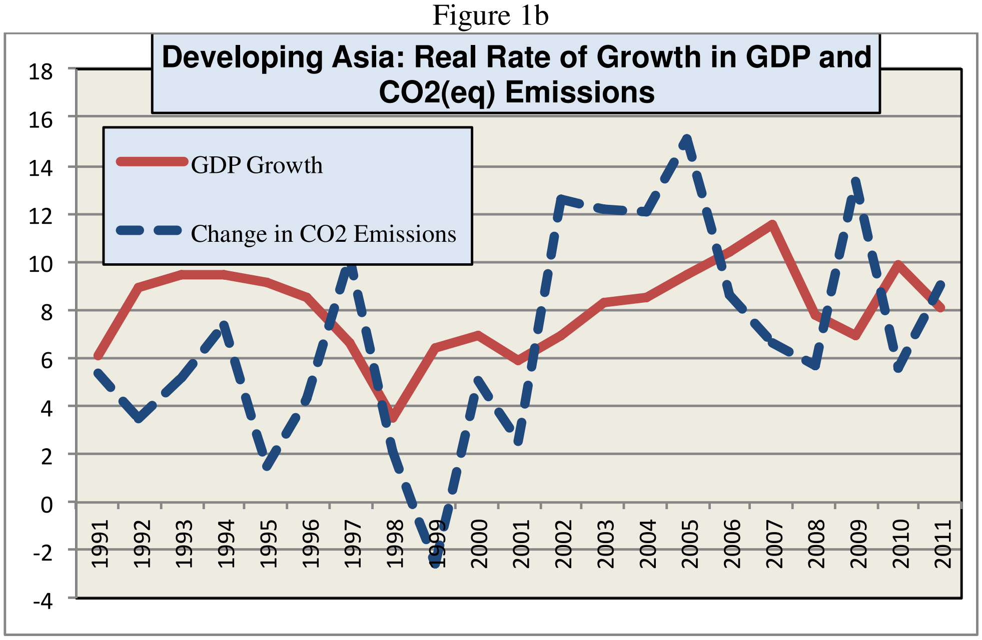
Figures 1a and 1b. CO_2 and GDP growth rates in Turkey versus Asian countries

Figure 1a



Source: Turkstat, Environmental Indicators

Figure 1b



Source: US International Energy Association and The IMF World Economic Outlook

A key hypothesis in this paper is that the projected lack of decoupling between growth and emissions mitigation is mostly driven by the uneven patterns of growth and industrialization across sectors in Turkey. Yeldan *et al.* (2013) suggest that one of the main causes of the productivity slowdown of the Turkish economy over the 2010s is due to the diverging patterns of regional and sectorial development and the widening gap across high versus low income regions, as well as modern versus traditional sectorial production (and consumption) patterns. We argue that the lack of mitigation at the aggregate national level finds its manifestation in the widening gap across regional and sectorial carbon and gaseous emissions.

To this end, we check for evidence on convergence of CO_2 emissions across sectors utilizing panel data econometrics over sectorial data. In continuation of evidence on convergence, if any, we search for the leading indicators of these processes by way of differentiating the production sectors according to their level of technology and energy utilization. The paper is organized as follows: in the next section we provide a brief survey on the theoretical background and pertinent literature. Next, we introduce our methodology and data sources in section three. We study alternative configurations of sectorial convergence in section four. We summarize the results and conclude in section five.

2. Background Theory and Literature

It is widely known that convergence in per capita income is rooted in the Solow model (Solow, 1956), which stipulates that countries (or regions) at lower per capita income levels are eager to experience higher growth rates than the richer ones due to the assumption of diminishing marginal returns to capital. The hypothesis has been tested frequently in the growth literature.

Inspired by the previous economic convergence research, environmental convergence literature devotes itself to investigate whether convergence between environmental indicators or the amount of pollutants (particularly, emissions) exists across various regions and time periods (e.g., Aldy, 2006; Ezcurra, 2007; Strazicich and List, 2003; Nguyen Van, 2005; Panopoulou and Pantelidis, 2007; Westerlund and Basher, 2008; Camarero et al., 2008; Brock and Taylor, 2010; and Camarero et al., 2013). The bulk of this research has focused on carbon convergence; by utilizing either cross-country data or panel data comprising of countries (see Pettersson *et al.* (2014) for a comprehensive review). The summary of this research prevails convergence in per capita carbon dioxide emissions to some degree between developed (OECD) countries, while evidencing relatively persistent gaps or divergence at the global level. Besides, studies on regional convergence have investigated patterns of pollutants across regions. For instance, List (1999) tests for convergence of SO2 and NOx for 10 US regions during the period 1929-1994 and finds limited evidence of convergence. Similarly, Lee and List (2004) conduct unit root tests for NOx in US states from 1900 to 1994 demonstrating that NOx emissions are not converging since the series are non-stationary and contain a unit root. Aldy (2007) and Bulte et al. (2007) are also among those who concentrate on US regional emissions.

Research on sectorial convergence remains relatively limited. Wang and Zhang (2014) study the per capita CO_2 emissions in 28 provinces and six sectors in China. They evidence convergence in all the sectors from 1996 to 2010; however they detect different factors that lead to convergence. For instance, GDP per capita and population density are the determinants of convergence in the industry sector as well as in the transportation, storage, postal, and telecommunications services sector. Apart from GDP per capita and population density, trade openness also influences convergence in the wholesale, retail, trade, and catering services. Finally, convergence of emissions due to residential consumption is mainly shaped by population density.

Another study that quests for sectorial emissions convergence is Moutinho, Robaina-Alves and Mota (2014), which analyzes CO_2 intensity of the Portuguese industry. The authors find sigma convergence for all sectors as well as provide evidence for the significant roles of fossil fuel use and energy consumption in determining sectorial CO_2 emissions and emissions intensity.

Finally, Brännlund, Lundgren and Söderholm (2015) investigate the convergence of CO_2 performance across the 14 Swedish manufacturing sectors from 1990 to 2008. They first calculate an environmental performance index derived from production of both the good and bad outputs. Then they estimate the growth of this index (*i.e.* the rate of change in the ratio of the inverse emission intensity) based on the initial value of the index and other factors such as sectorial capital intensity, fossil fuel use, fossil fuel price, value-added and EU ETS participation. They detect conditional β-convergence in CO_2 performance together with the contribution of higher fossil fuel prices to improved CO_2 performance in the Swedish industrial sectors whereas they find no significant effect of EU ETS participation.

Despite not searching for convergence, Kumbaroğlu (2011) conducts a sector decomposition analysis of Turkey's CO_2 emissions during the period 1990-2007, and highlights the scale effect as the major source of emission growth in the electricity, manufacturing and transport sectors. He attributes emission growth in the household and agriculture sectors to energy intensity.

Yet, to the best of our knowledge, this is the first study to undertake an analysis of sectorial carbon convergence in Turkey. In what follows, we introduce the methodology and data sources in the next section.

3. Methodology, Data and Sources

The notion of convergence can be investigated through three concepts: sigma (σ), beta (β), and stochastic convergence. To begin with, Barro and Sala-i-Martin (1992) describe σ-convergence as the decrease in the cross-section variance of per capita emissions over time. Up to this aim, cross-sectional variance or standard deviation is simply plotted to detect convergence. Other studies have examined the behavior of relative per capita emissions (RE_{it}), where the relative per capita emissions is measured as the log of one country's or sector's emissions at time t divided by the yearly sample average $\bar{y}_t$, as notated by Carlino and Mills (1993) as follows:

$$RE_{it} = \ln(y_{it} / \overline{y}_t) \tag{1}$$

Second, using time series analysis, stochastic convergence can be explored to detect whether shocks to emissions for country or sector i relative to another country or sector j (or the average of the sample) are temporary (see Pettersson et. al (2014) for further details). If the time series of interest does not contain a unit root and is proven to be trend stationary, the series is found to be stochastically converging. Many studies including Strazicich and List (2003), Lanne and Liski (2004), McKitrick and Strazicich (2005), Romero-Ávila (2008), Westerlund and Basher (2008), Lee and Chang (2008), Nourry (2009), and Yavuz and Yilanci (2013) make use of various unit root tests to trace stochastic convergence of emissions in different samples of countries. This method can also be implemented for panel data by using panel unit root techniques, which will be employed in the next section of the current study.

Finally, β-convergence can be investigated both in a cross-section and panel data setting. The cross-sectional approach implies that convergence is examined by regressing the logged period growth rate of emissions (y_{it} / y_{i0}) (for the whole sample) on the *initial* logged emission levels y_{i0} and an error term ε_i for country, region, or sector i as in below (Pettersson et al. 2014: 150):

$$\ln(y_{it} / y_{i0}) = \alpha + \beta \ln(y_{i0}) + \varepsilon_i \tag{2}$$

where ε_i is the error term for country or region i. Accordingly, $\beta < 0$ implies convergence. Similarly, panel β-convergence can be analyzed as in the following equation (Pettersson et al. 2014: 151):

$$\ln(y_{it} / y_{i,t-1}) = \alpha' + \beta' \ln(y_{i,t-1}) + \delta_i + \varepsilon_{it} \tag{3}$$

where $\ln(y_{it} / y_{i,t-1})$ is the growth rate of emissions between $t-1$ and t, and δ demonstrates sector-specific effects. This model specification helps to test whether emission growth rates converge across cross-section units by time; *i.e.* whether they are eager to slow down in the long-run as they approach their own long-run growth path.

In our investigation of β-convergence, we utilize two separate emissions indicators, one being the growth rate of sectorial emissions (CO_2) and the other being the growth of sectorial emission intensity defined as the ratio of CO_2 emissions to sectorial value-added (CO2/VA). Alongside, we focus on the coefficient (β) of the previous emissions and emission intensities respectively in the search for convergence, where the null hypothesis of divergence is H_0: $\beta = 0$ for all i; and the alternative hypothesis of convergence is H_a: $\beta < 0$ for all i. A negative sign for β implies unconditional convergence in CO_2 emissions. Adding control variables such as sectorial value-added (VA), capital stock (KSTOCK) and energy use (EN) to equation (3) entails testing conditional convergence.

Our models are estimated via panel fixed-effects and dynamic panel (Arellano-Bond) specifications. Panel convergence has frequently been addressed by either fixed or random effects in the literature. However, it is plausible to include some dynamic effects into the standard panel model since growth of emissions accommodates dynamic effects with respect to the previous emission growth rates. In econometric theory, these dynamic effects can be integrated into the model via the inclusion of a lagged dependent variable among the regressors. While doing so, the lagged dependent variable might be correlated with the error term especially in small samples, which comes out as a problem. An instrumental variable specification is preferred to tackle with this problem and more specifically, the Generalised Method of Moments (GMM) model can be employed using the lagged values of the variables in the original model as instruments. Among several approaches to dynamic panel data models, Arellano-Bond specification is the most commonly used one. It accounts for individual or fixed effects by differencing the data. Besides, it is the more favourable approach and results in consistent estimates when the number of cross-sections, *N*, is higher than the number of time periods, *T*. (Baltagi, 2005: 136).

The sectorial variables used in the models are described in Table 1 below:

Table 1. Variables used in the analysis

Abbr.	Definition of the variable	Unit	Data source
CO2	CO_2 emissions	Gg (kt)	WIOD
VA	Sectorial Value-added	TLs (million)	WIOD
KSTOCK	Capital stock	TLs (million)	WIOD
EN	Emission relevant energy use in)	TJ	WIOD

All our data are adapted from the World Input-Output Database[1] (WIOD), and is further supplemented by the Turkstat data on CO_2 emissions. The names and the classification of the sectors that are under consideration are provided in Appendix A2. The summary of descriptive statistics for the variables of interest is provided in Appendix A3. We further classify our sectors in terms of their technology levels, as primary (low), medium and high technology-driven activities. This categorization is based on the OECD classification of technology adoption. WIOD data reveals that, the bulk of the manufacturing sectors display medium technology characteristics and the share of medium technology sectors account for 81% of total value added in 2013 (see Table 2 below).

Table 2: Value added shares of sectors according to technology utilization

	value added shares	
	1995	**2013**
Primary/Low Technology Sectors	0.18	0.11
Medium Technology Sectors	0.74	0.81
High Technology Sectors	0.08	0.08

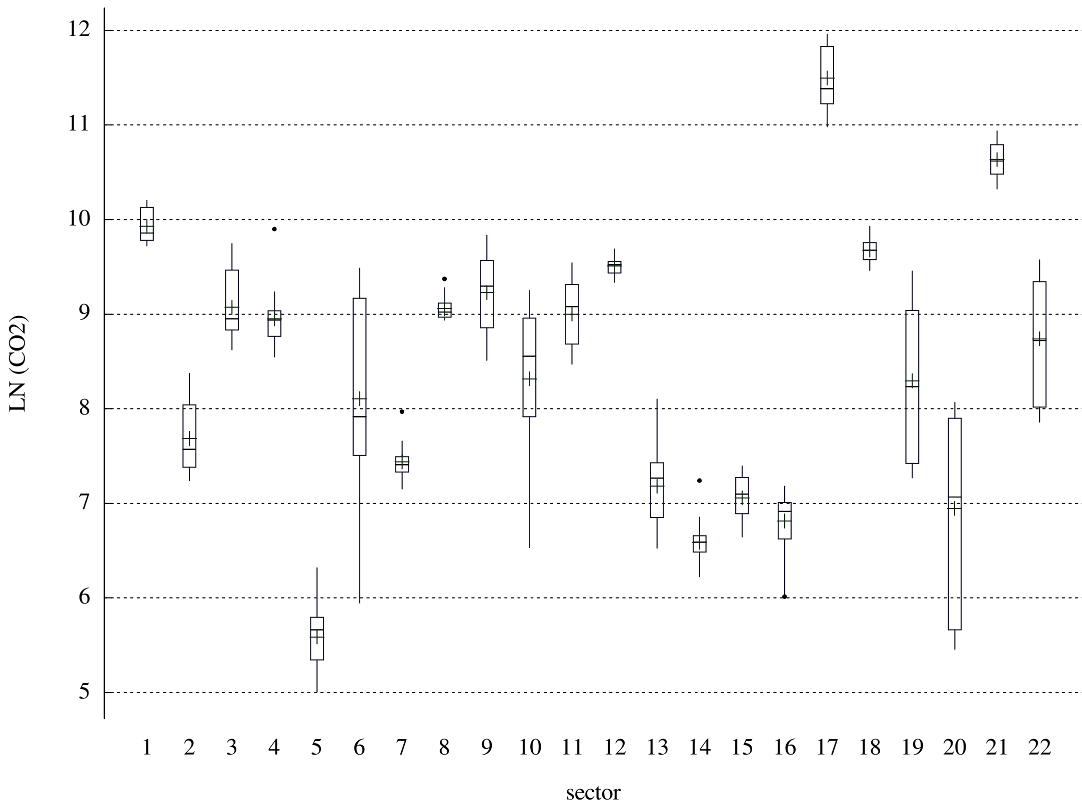
Source: WIOD data based on the OECD classification of technology adoption.

Figure 2 further displays the distribution of sectorial CO_2 emissions in Turkey over the sample period. In absolute emissions, Electricity, Gas and Water Supply (no.17) and Transport (no.21) stand out as the prominent sectors, whereas Leather and Footwear (no. 5) is the least emitting sector. The time dispersion of the emissions is the widest for Hotels and Restaurants (no.20) as well as Wood and Products of Wood and Cork (no.6) as illustrated in the box plot. The boxes are bounded by the first and third quartiles of the data, enclosing the middle 50% of the sample. The dots illustrate the outliers; the lines across each box show the medians; and the "+" signs indicate the "mean" observations for each sector. It is revealed that the sectors

[1] See Timmer et al (2015) and the website http://www.wiod.org/new_site/home.htm for the details of the WIOD.

under consideration behave quite differently in their mean and median emissions during the 1995-2013 period. When we compare sectorial emissions with respect to sectorial value-added amounts, Coke, Refined Petroleum and Nuclear Fuel (no.8) and Electricity, Gas and Water Supply (no.17) are noticeably the sectors which are performing badly. Other economy[2] (no.22) releases the lowest amount of CO_2 per value-added among other sectors.

Figure 2. Sectorial CO_2 emissions distribution for 1995-2013



Note: The names of the sectors from 1 to 22 corresponding to the x-axis are provided in Appendix A2.

4. Empirical Results on Patterns of Convergence of Sectorial Gaseous Emissions

4.1. σ-convergence

In order to perform a distributional analysis of emissions in the Turkish sectors, we plot the natural logarithm of the ratio of CO_2 in each sector divided by average CO_2 emissions in all sectors in that year, *i.e.* log relative emissions. To that end, Figure 3 demonstrates signs of convergence to some extent, especially accelerating following the recent global crisis. It has to be noted, in this juncture, that the 2008/09 crisis had a profound impact on the nature of this convergence. Figure 4 is a direct illustrator of this phenomenon, where average log relative CO_2 emissions for all sectors increase initially, make a peak in 2003, decline

[2] Other economy comprises of the following sectors: Post and Telecommunications; Financial Intermediation; Real Estate Activities; Renting of Machinery and Equipment and Other Business Activities; Public Administration and Defence; Compulsory Social Security; Education, Health and Social Work; Other Community, Social and Personal Services; Private Households with Employed Persons.

substantially afterwards, and hit the bottom in 2008. There has been a recovery in mean sectorial emissions following the global turmoil.

Figure 3. Evolution of log relative CO_2 emissions in each sector, 1995-2013

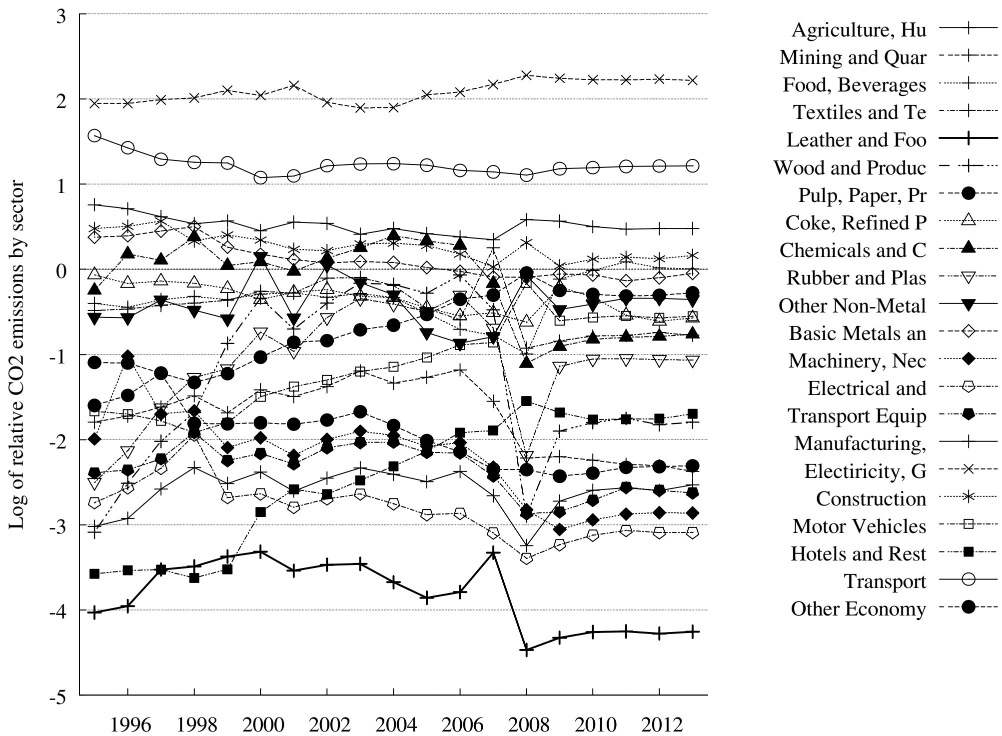
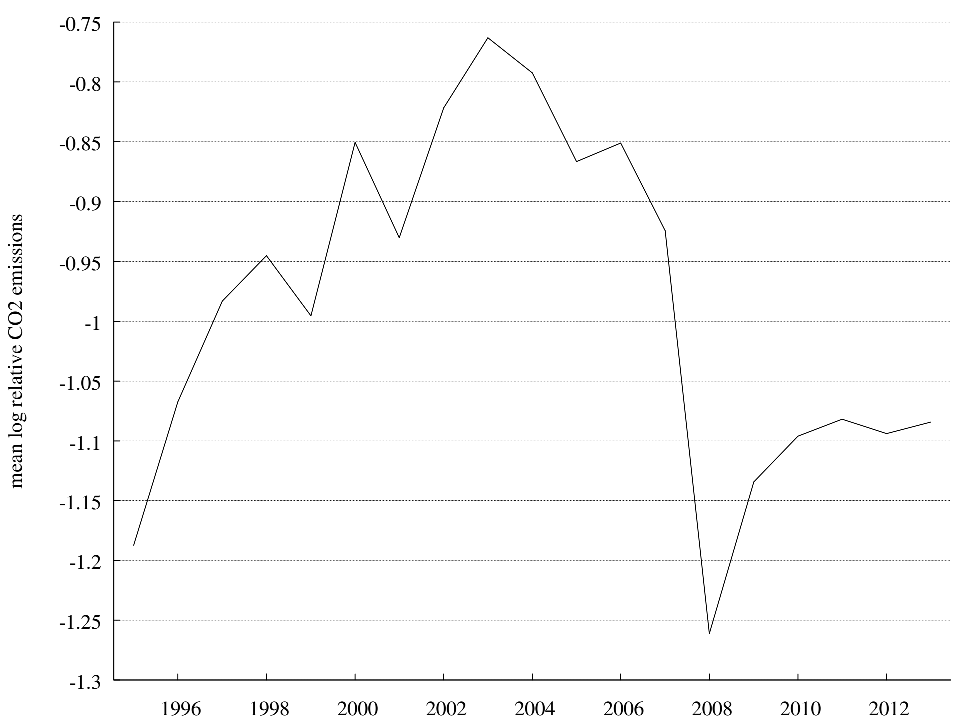


Figure 4. Mean log relative CO_2 emissions for all sectors by year



Finally, as suggested by Barro and Sala-i-Martin (1992), Table 3 displays σ-convergence formulated by "standard deviation", which serves as a measure of cross-sectional variation of per capita emissions over time. Apparently, the standard deviation of emissions decreased by 7% from 1995 to 2013, documenting sigma convergence in the sectors.

Table 3. Standard deviation of cross-sectorial CO_2 emissions from 1995 to 2013

	1995	2013	% Change between 1995 and 2013
Standard deviation of cross-sectorial (log) CO_2 emissions from 1995 to 2013	1,66	1,55	-7%

4.2. Stochastic convergence

In order to test for stochastic convergence, we first test for cross-sectional dependence for the three relevant variables derived from the sample: natural log of CO_2 emissions (LNCO2), CO_2 emissions as a share of sectorial value-added (CO2/VA), and log relative CO_2 emissions (LNRELCO2). The results are displayed in A4. Accordingly, we run first generation panel unit root tests for CO2/VA as we cannot reject cross-section independence, whereas we run second generation panel unit root tests for LNCO2 and LNRELCO2 as the cross-sections for these variables exhibit cross-section dependence.

Among several first generation panel unit root tests, Im-Pesaran-Shin (IPS) (2003) and Breitung (2000) tests, which are the two widely used panel unit root tests, are employed here. The methodology is as follows. Considering an AR (1) process for panel data, y_{it} is modeled as:

$$y_{it} = \rho_i y_{it-1} + X_{it}\delta_i + \varepsilon_{it} \tag{4}$$

where t and i stand for time and cross section units, respectively. Individual unit root tests such as IPS, Fisher-ADF, and Fisher-PP allow differing ρ_i across cross-sections, whereas common unit root tests such as LLC, Breitung and Hadri assume a common unit root process, thereby taking identical $\rho_i = \rho$ across cross-sections, *i.e.* for all i. IPS test provides individual tests for each series. The null and alternative hypotheses of the IPS test are as follows: *Ho: All panels contain unit roots. Ha: Some panels are stationary.* In other words, IPS assumes that at least one of the series is stationary under the alternative hypothesis. On the other hand the corresponding hypotheses for the Breitung unit-root test are stated as follows: *Ho: Panels contain unit roots. Ha: Panels are stationary.* Breitung illustrates that the IPS tests suffers from a significant loss of power when individual-specific trends are included to the test and his alternative test statistic "does not employ a bias adjustment" (Baltagi, 2005: 243). As such, the Breitung test implies stronger results than the IPS. In both tests, the rejection of a unit root and the presence of stationarity imply convergence, whereas the non-rejection of a unit root implies divergence.

For LNCO2 and LNRELCO2, we employ Pesaran's CADF test (2007), which is a second generation panel unit root test. The test allows the individual autoregressive roots to differ across the cross-sectional units and is normally distributed under the null hypothesis of non-stationarity.

Table 4. Panel unit root tests

		LNCO2	CO2/VA	LNRELCO2
IPS test statistic	With a drift and trend		-0.7533 (0.2256)	
	Without a drift, with trend		**-2.3591 (0.0092)**	
	With a drift, without trend		**-1.7694 (0.0384)**	
	Without a drift and trend		2.8945 (0.9981)	
Breitung test statistic	With a drift and trend		0.4861 (0.6866)	
	Without a drift, with trend		0.2554 (0.6008)	
	With a drift, without trend		**-1.8267 (0.0339)**	
	Without a drift and trend		1.2558 (0.8954)	
Pesaran's CADF test statistic	Constant	-0.426 (0.335)		-1.247 (0.106)
	Constant and trend	-0.0667 (0.252)		-0.942 (0.173)

p-value in parentheses.

According to Table 4, the IPS and Breitung test results for CO2/VA suggest that unit roots cannot be rejected in the majority of the specifications, implying non-stationarity and hence, stochastic divergence. However both tests imply convergence when the series are de-trended. Pesaran's CADF test also shows that sectorial emissions and relative emissions in logarithms do not converge as the null hypothesis of unit roots cannot be rejected. To sum up, these results provide strong support for a diverging pattern in sectorial emission levels and poor evidence for convergence in emission intensity.

4.3. β-convergence

As described in section three, β-convergence is analyzed via panel data regression techniques here. Table 5 demonstrates the results of the analyses which are undertaken for the whole sample. Models 1_FE and 1_AB represent Fixed Effects and Dynamic GMM (Arellano-Bond) models respectively with the growth rate of log sectorial CO_2 emissions as the dependent variable; whereas 2_FE and 2_AB represent the corresponding models with growth rate of CO2/VA as the dependent variable. Accordingly, the independent variables are in natural logarithms in models 1_FE and 1_AB, while they are transformed into shares in value added of each sector in models 2_FE and 2_AB.

The results imply conditional β-convergence in all cases, with the exception of 1_FE, with slight differences regarding the effects of the explanatory variables. It appears that sectorial energy use increases the emissions growth rate significantly whereas industrial value added decreases emissions growth rate contributing to convergence in model 1_AB. This might stem from the existence of economies of scale as the industry produces higher value added. That is to say, when the sectors have a lower output level, they would produce some amount of the "bads", *i.e*. emissions. As sectors grow, they do not necessarily increase their amount of CO_2 proportionally to their output growth since they would require relatively less energy or other inputs per output as the production scale increases. Besides, sectorial capital stock has a slightly significant positive impact on the growth of emissions in only one of the models (1_AB).

Table 5. Fixed effects and dynamic panel data estimation (Arellano-Bond) results for the whole sample

	(1_FE) Growth of CO2	(1_AB) Growth of CO2	(2_FE) Growth of CO2/VA	(2_AB) Growth of CO2/VA
CO2_1	-0.190***	-0.222***	-0.012***	-0.006**
	(-2.73)	(-3.98)	(-4.35)	(-2.41)
VA_1	-0.049	-0.053*		
	(-1.08)	(-1.94)		
KSTOCK_1	0.009	0.053*	0.00001	-0.0002
	(0.19)	(1.91)	(0.03)	(-0.84)
EN_1	-0.112	0.197***	0.0009***	0.0006**
	(-1.23)	(3.20)	(3.14)	(2.40)
Constant	3.059***	-0.469**	0.126***	0.053**
	(4.89)	(-2.03)	(2.77)	(2.11)
Observations	396	396	396	396
F	21.26		12.90	
P > F	0.000		0.000	
r2_o	0.017		0.006	
chi2		20.95		7.19
P > chi2		0.000		0.066
Sargan		315.24		316.37
sarganp		0.847		0.795
ar1		-1.97		-11.06
ar1p		0.049		0.000

t statistics in parentheses. Denotations (F:F-Value, r2_o:Overall R-Square, chi2:Chi-Square, p:P-Value)
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Finally, Table 6 displays the results of the convergence analysis in three sectors classified according to their technology levels: primary (low) technology (LOWTEC), medium technology (MEDTEC) and high technology (HITEC). As the number of observations does not satisfy model assumptions, we are not able to conduct a dynamic analysis for the specified sectors. Hence we proceed with panel fixed effects.

The results imply that the sample of medium-tech sectors does not support β-convergence in CO_2 emission levels, whereas low- and high-tech sectors experience absolute convergence (although low-tech sectors do not have a highly significant coefficient for their past emissions, implying weaker convergence). The lack of support for convergence in the absolute level of emissions of medium technology sectors, which consist of the bulk of the Turkish manufacturing industries, is clearly the main driving factor in the relatively low degree of convergence at the aggregate level (observed via the corresponding beta coefficients above).

When we deal with emission intensities (CO2/VA) instead, we find that the medium-tech and high-tech sectors provide evidence for convergence while low-tech sectors do not. It can be argued that the convergence as observed within the high technology sectors can be attributed to their dynamic and open character. Openness and relative ease in access to advance technology would have helped these sectors to internalize the external economies of scale and thereby reduce their pollution intensities. On the other hand, capital stocks in the high-tech sectors play a positive role in accelerating the growth rate of CO2/VA.

Table 6. Fixed effects estimation results for sectors classified with respect to technology

	LOWTEC Growth of CO2	MEDTEC Growth of CO2	HITEC Growth of CO2	LOWTEC Growth of CO2/VA	MEDTEC Growth of CO2/VA	HITEC Growth of CO2/VA
CO2_1	-0.426*	-0.124	-0.694***	-0.050	-0.009**	-0.021**
	(-1.71)	(-1.54)	(-2.94)	(-1.66)	(-2.52)	(-2.46)
VA_1	-0.363	-0.014	-0.054			
	(-0.90)	(-0.18)	(-0.87)			
KSTOCK_1	0.287	-0.025	-0.131	0.001	-0.001	0.006**
	(1.30)	(-0.38)	(-0.92)	(0.31)	(-1.12)	(2.55)
EN_1	0.218	-0.183	0.376	0.003	0.000	0.001
	(0.82)	(-1.65)	(1.33)	(1.03)	(0.56)	(1.55)
Constant	0.499	3.416***	3.319**	0.189	0.289***	-0.055
	(0.33)	(4.20)	(2.62)	(0.54)	(3.41)	(-0.48)
Observations	54	270	72	54	270	72
F	1.813	13.199	8.074	2.236	11.565	4.584
p > F	0.117	0.000	0.000	0.066	0.000	0.001
r2_o	0.000	0.013	0.075	0.098	0.005	0.015

t statistics in parentheses. Denotations (F:F-Value, chi2:Chi-Square, p:P-Value, r2_o:Overall R-Square)
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. Conclusion

In this paper we searched for the existence and nature of convergence of carbon dioxide emissions for the Turkish economy under conditions of uneven growth. We applied a series of econometric tests to deduce patterns of convergence, both at the aggregate –economy-wide level, as well as across sectors.

The simplest metric we utilized was the measure of standard deviations from the mean, *i.e.*, the "σ-convergence". This measure was found to indicate convergence in the aggregate. A closer investigation reveals that the main driving factor behind this result had been the business cycle. In particular, the repercussions of the 2009 global crisis are observed to have a profound impact on accelerating the convergence of the CO_2 emissions by way of evening out the fluctuations of the aggregate economic activity.

Second we focused on the dynamics of stochastic convergence. This analysis was carried both on the *level* of CO_2 emissions, and also on CO_2 intensity, *i.e.*, CO_2 per value added (CO2/VA). We found that sectorial CO_2 emissions per unit of value added depict stochastic convergence (when de-trended) corroborating our finding that the CO_2 emissions follow the business cycle. At the aggregate level of CO_2 emissions, however, patterns of convergence are dissipated and give way to a diverging trend. We then searched for evidence on *conditional convergence*, the so-called *β*-convergence. Here we regressed the rate of growth of the *level* of CO_2 emissions on the one period lagged value of the following explanatory variables: CO_2, value added, physical capital stock, and energy utilization. In a second variant of this model, the rate of change of CO2/VA intensities were regressed against the per unit value added ratios of the same variables, K/VA and EN/VA. Our results implied conditional convergence in most of the cases specified. Energy use appeared to be the most prominent indicator that drove emissions growth and emission intensity growth in the whole sample.

Finally, we distinguished the aggregate economy under a three-tier sectorial specification based on their technology characteristics: low, medium, and high. We find that while the high technology sectors display strong convergence, the medium technology sectors –the bulk of Turkey's economy accounting for 80% of the aggregate value added, does not support *β*-convergence in CO_2 emission levels. Our results further revealed that the physical capital stock fails to generate a statistically significant impact on CO_2 emissions (except its positive role on the high-tech sectors' emission intensities). This is an unexpected result given the rather strong capital intensity of the Turkish growth path, especially over the 2000s. We interpret these observations as a result of the lack of any viable de-coupling due to the persistent structural reliance on energy resources with heavy coal and fossil intensities.

Several policy implications could be derived from these results. First, since the emission growth rates are mostly attributable to the energy intensities in the sectors, it appears necessary to reconsider the patterns of energy use taking into account the fact that fossil fuels are currently the most dominant energy sources for these sectors. Second, as technology level makes a difference in the convergence characteristics, the country could try to transform or diversify its technological sophistication towards cleaner options. Last but not the least, a sectorial CO_2 convergence analysis of this kind might provide insights about the impacts of relevant energy and climate policies on industries with differing characteristics with respect to technology, capital composition and energy use.

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Appendix

A1. Turkey's greenhouse gas emissions by sectors (CO_2 equivalent), 1990 – 2013 (million tonnes)

Year	Energy	Industrial processes and product use	Agriculture	Waste	Total	Change compared to 1990 (%)
1990	131,6	31,1	41,6	13,9	**218,2**	
1991	135,6	32,5	42,3	14,5	**224,9**	3,1
1992	141,3	31,9	42,5	15,1	**230,8**	5,8
1993	149,1	32,3	43,4	15,7	**240,5**	10,2
1994	145,6	32,0	40,7	16,3	**234,6**	7,5
1995	158,8	33,7	40,2	16,9	**249,5**	14,4
1996	173,9	35,4	41,2	17,5	**268,0**	22,9
1997	187,0	37,3	39,5	18,3	**282,1**	29,3
1998	186,6	37,1	41,3	18,9	**283,8**	30,1
1999	186,3	35,8	41,7	19,8	**283,7**	30,0
2000	213,8	36,2	40,1	20,7	**310,8**	42,5
2001	197,2	36,6	37,4	21,5	**292,7**	34,1
2002	205,2	37,8	36,2	22,2	**301,3**	38,1
2003	218,2	41,0	37,6	22,8	**319,7**	46,5
2004	228,5	43,4	37,5	23,7	**333,1**	52,7
2005	251,8	46,9	38,5	24,6	**361,7**	65,8
2006	275,1	48,4	39,5	25,6	**388,6**	78,1
2007	306,4	50,2	39,0	26,2	**421,8**	93,4
2008	294,2	52,6	36,9	26,6	**410,4**	88,1
2009	280,5	54,9	38,5	26,9	**400,7**	83,7
2010	284,8	60,0	39,8	27,2	**411,7**	88,7
2011	297,6	65,6	41,6	27,7	**432,5**	98,2
2012	320,8	69,6	46,3	27,6	**464,2**	112,8
2013	311,2	72,0	49,8	26,0	**459,1**	110,4

Source: TurkStat, Greenhouse Gas Emissions Inventory, 2013

A2. Codes and classification of the sectors included in the analysis

Code	Sector	Technology classification
1	Agriculture, Hunting Forestry and Fishing	Primary / Low Technology Sectors
2	Mining and Quarrying	Primary / Low Technology Sectors
3	Food, Beverages and Tobacco	Primary / Low Technology Sectors
4	Textiles and Textile Products	Medium Technology Sectors
5	Leather and Footwear	Medium Technology Sectors
6	Wood and Products of Wood and Cork	Medium Technology Sectors
7	Pulp, Paper, Printing and Publishing	Medium Technology Sectors
8	Coke, Refined Petroleum and Nuclear Fuel	High Technology Sectors
9	Chemicals and Chemical Products	High Technology Sectors
10	Rubber and Plastics	High Technology Sectors
11	Other Non-Metallic Mineral	Medium Technology Sectors
12	Basic Metals and Fabricated Metal	Medium Technology Sectors
13	Machinery, Nec	Medium Technology Sectors
14	Electrical and Optical Equipment	High Technology Sectors
15	Transport Equipment	Medium Technology Sectors
16	Manufacturing, Nec; Recycling	Medium Technology Sectors
17	Electricity, Gas and Water Supply	Medium Technology Sectors
18	Construction	Medium Technology Sectors
19	Motor Vehicles	Medium Technology Sectors
20	Hotels and Restaurants	Medium Technology Sectors
21	Transport	Medium Technology Sectors
22	Other Economy	Medium Technology Sectors

A3. Summary Statistics, using the observations for 22 sectors, 1995-2013

Variable	Mean	Median	Minimum	Maximum
CO2	12480.1	5882.59	148.788	156260.
VA	722.708	361.997	30.4871	6575.96
KSTOCK	70352.6	28491.0	868.044	440838.
EN	129908.	73017.7	2140.02	1.47989e+006
Variable	**Std. Dev.**	**C.V.**	**Skewness**	**Ex. kurtosis**
CO2	23219.4	1.86051	3.96951	17.6107
VA	981.395	1.35794	3.05638	11.3172
KSTOCK	95118.8	1.35203	2.00949	3.07307
EN	229656.	1.76784	3.92973	16.9772
Variable	**5% Perc.**	**95% Perc.**	**IQ range**	**Missing obs.**
CO2	331.202	55745.0	11338.5	0
VA	56.5941	2519.86	618.174	0
KSTOCK	2281.85	316989.	75118.7	0
EN	6687.27	545754.	109629.	0

A4. Pesaran (2004) cross-section dependence tests

Variable	CD-test	p-value	corr	abs(corr)
LNCO2	15.51	**0.000**	0.234	0.422
CO2/VA	0.90	0.369	0.014	0.485
LNRELCO2	4.04	**0.000**	0.061	0.473

Null hypothesis: There is cross-section independence.