Analysis of carbon productivity for firms in the manufacturing sector of India

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Abstract

Emission estimation and carbon productivity at the firm level for India's manufacturing sector are scanty. We fill this gap by estimating CO_2 emissions at the firm level and further determining the optimal and the actual trade-offs between emissions and output at the firm level. We use data from the Center for Monitoring Indian Economy (CMIE) Prowess IQ, and MoEF&CC, Government of India. Between 1998 to 2019, growth in CO_2 emission and output is estimated to be 3 and 9 per cent, respectively. This indicates a case of weak decoupling for the manufacturing sector where technology, export promotion strategies, environmental taxes, energy mix at the firm level, and cap-and-trade policy are the significant determinants of carbon productivity for the sample firms in India's manufacturing sector. We conclude that improving carbon productivity is necessary for better decoupling and R&D intensity to be complemented with R&D efficiency to gain carbon productivity for the manufacturing industry. These findings are crucial for better energy and climate policy for the Indian economy.

Keywords: Carbon productivity; energy efficiency; decoupling growth; threshold regression; club convergence

JEL Classification: Q53. Q54. Q55. Q57

1. Introduction

Climate policy is one of the crucial goals for policymakers (Pachauri and Reisinger, 2008). In this context, optimal emission policy contributes to economics literature (Oates, 1995). On the contrary, the Paris Agreement has turned out to be a non-cooperative game between economies, and hence country-specific solutions are suggested as a mitigation effort.[5] Literature in these lines for the Indian economy is rather scanty. India has become the third-highest global emitter, after China and the US. India emitted 2.62 billion tons of CO_2 (around

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7 per cent of the Global emission) during 2019. Given the size of the GDP of the Indian economy, India is eligible to receive funds for environmental expenses. These two characteristics make the Indian economy vital for a detailed analysis. However, as data is still not available at the firm level on emissions, most existing studies focus on using a proxy for emissions or analysis at aggregate levels. Deviating from the current studies, we estimate carbon emissions, carbon productivity and optimal emission policy at the firm level to fill the research gap. As the Indian economy has "*missed the manufacturing bus*", we focus on the sectoral levels (Cantore et al., 2017; Ministry of Finance, 2015). There is a scope to enhance the manufacturing sector's performance by improving the emission policy, which will help the mitigation goals, besides attaining the "*Making in India*" goals (Bhattacharya et al., 2018). The novelty of this paper lies in estimating the CO_2 emission of the Indian manufacturing firms since the Kyoto protocol until the latest available data. Either the standard literature has focused on emission control or improving carbon productivity, but often these two becomes contradictory. In this paper, we solve the puzzle by analyzing the following objectives:

1. Explain the trade-off between emission and growth for the Indian manufacturing sector.
2. Explain factors affecting the trade-off to help in strategizing policies.
3. Identify the inter-firm heterogeneity in CO_2 emission.

The first objective of this paper contributes to the ongoing debate on optimal emission policy. As there is a trade-off between output and emission levels, this paper's results will benefit the policy context in the Indian economy. However, there is a crucial question to address if there is a gap between the optimal and the actual emission from firms. This is investigated in the second objective of this paper. The second objective will help us determine the importance of demand and supply-side factors on emission control in general and the tole of technology and price in particular. Among other things, it's also essential to explain the inter-firm heterogeneity in emission. This is essential to define the macro-policy for the industrial sector of the Indian economy.

The remainder of the paper is as follows. Section 2 discusses a brief literature review, section 3 discusses the empirical setting, section 4 presents the empirical results, and section 5 concludes with possible policy suggestions.

2. Review of literature

Climate change and emission have ignited the debate on optimal emission. In this context, recent suggestions for the cost practical climate mitigation goal focuses on strengthening carbon productivity (Bai et al., 2019; Li and Wang, 2019; Li et al., 2018). The study on carbon productivity was initiated during the late 1990s (Kaya and Yokobori, 1997). Later, carbon intensity is focused in the literature as an alternative or proxy to carbon productivity (Sun, 2005). The main aim for explaining carbon productivity is to link it with the policy goals, especially at the sectoral level (Li et al., 2018). Such analysis helps decide the optimal trade-off between emission and output (Beinhocker et al., 2008; Meng and Niu, 2012). This implies that such studies contribute to emission control and help foster economic growth and employment through cost-efficient mitigation efforts (Bhattacharya et al., 2018).

Nonetheless, the findings vary, depending on multiple factors, such as types of data, time-frame, methods, variables used across studies. Hence, sector-specific approaches are fundamental to be analyzed. In this context, China and India gained special attention, specifically after the Paris agreement (Tapio, 2005), though studies investigating such issues in India are negligible compared to the Chinese literature (Fang and Yu, 2021; Herrerias et al. 2013; Liu et al., 2017). Studies have suggested that sector-level policies benefit carbon productivity for the Chinese economy (Lin and Jia, 2019; Zhao and Lin, 2019; Zheng and Lin, 2020). Carbon emission rights are allocated for China’s six high-energy-consuming industries (Wu et al., 2020). They conclude that electric power and the iron & steel industries show the most significant potential for emissions reduction instead of the transport industries. In this case, they suggest a “*high economic growth and low energy consumption*” scenario for the sustainable growth of the industrial sector. Most recently, the social cost of carbon has been investigated for China (Zhang et al. 2021). Studies have identified decision-making, equity weight, uncertainty, risk aversion, and discount and time preference rates have a higher impact on the social cost of carbon (Wang and Luo, 2020).

Further, a “*weak*” Porter hypothesis for specific listed companies in 31 provinces in China was also estimated and explained (Dong et al., 2013). This study concludes that companies mainly choose to reduce output instead of increasing green technological innovations to achieve emission reduction targets. Their conclusions align with the suggestions of climate scientists and policymakers for improving carbon productivity (Hu and Liu 2016; Meng and Niu, 2012) from the industrial sector.

Due to the absence of emission data, Indian studies are mostly confined to energy and output trade-offs as a proxy (Sahu et al., 2021; Sahu and Narayanan, 2014). Minimal investigations in the Indian context have been attempted in this line. For example, studies have focused on a social accounting approach and the input-output method on the carbon emission scenarios for India (Li et al., 2018). Studies, such as (Ryan, 2018; Sahu and Mehta, 2018; Sahu and Narayana, 2010), have examined emissions for the manufacturing sector in India. Most of the findings suggest energy consumption patterns as one of the significant drivers of carbon emissions. However, most of these studies have not explained the degrees of proximity.

Carbon productivity is explained from the decoupling growth theory (Chen et al., 2020). The current literature on carbon productivity and emission control has three significant findings: (1) technology is the critical driver (Meng and Niu, 2012); (2) price instruments, i.e. tax/cap-and-trade/hybrid pricing are helpful (Hu and Liu, 2016); and (3) have directly related to productivity and associated factors (Zhengnan et al., 2014). Among all these factors, technological advancement and technology have gotten the maximum attention from the scientific committees and the economic literature on adaptation or mitigation. The traditional understanding is that innovation, R&D, green adoption help improve carbon productivity (Dong et al., 2013; Du and Li, 2019). It is also suggested that they generally fail to attain impressive carbon productivity due to lower investment in technological development. Hence, it is essential to examine the nature of technological development on emission control in the developing economies as strategies are taken by developed countries may not produce similar results in the developing or underdeveloped nations, and thereby, national targets are essential (Bjørn et al., 2018; Li et al., 2018).

Studies investigating the relationship between technology and emission control in the decomposition approach have gotten sufficient attention in the recent literature (Wang and Feng, 2018). Since the last decade, the idea of the decomposition approach has been extended to check the contribution of various other economic factors on carbon productivity (Ma et al., 2019; Ma et al., 2020; Wang et al., 2015; Zhang et al., 2020). These studies identify the changes in carbon productivity in terms of economic activities and technological production changes. For example, technological progress is a crucial driver for improving inter-regional disparities in carbon productivity in China during 2005–2015 (Chen, 2020). Such studies are highly impactful for policy making. This leads to the research gap on understanding the context for the Indian economy, which is vital to prescribe policies for emission control with cost-efficient solutions that may induce the stagnant manufacturing growth of India (Bhattacharya et al., 2018). Indian studies recently focused on the growth path to propose mitigation policy (Bhattacharya et al., 2018). They discuss energy productivity and offer club-specific solutions for the Indian states. Bai et al. (2019) use a similar econometric analysis to explain carbon productivity from 1975 to 2013 for 88 economics. However, these studies are highly influenced by green investments and bypass the inter-linkage between emission, technology, and economic factors (Kim, 2015; Yu et al., 2015). As sectoral level analysis is scanty for the Indian economy, it is crucial to analyze carbon productivity at the sectoral and firm levels.

3. The empirical setting

For various years, we collected data from the Centre for Monitoring Prowess (CMIE) Prowess-IQ and the Ministry of Environment, Forest, and Climate Change (MoEF&CC), Government of India. CMIE registers the firm-level data annually. Our data covers from 1998 to 2019. Data on energy consumption (both economic and physical units), gross sales (Y) and net sales (Q), factor inputs (labour, capital, material, and energy), R&D expenditure, expenditure on imported goods, royalties and technical fees, exports, and profits are primary data of interest from the CMIE. Based on the pollution loads, data on industrial classification are taken from the MoEF&CC. These pollution loads are matched with the 5-digit National Industrial Classification of the Government of India. Since few firms report physical energy consumption data, we left with 31,000 observations. This represents unbalanced panel data; however, as our analysis requires firmly balanced data, we arrive at 1,496 observations from 1998-2019 for our study. We describe our sample in table 1.

3.1 Variables description

We use energy efficiency (EE) (Lin and Jia, 2014; Wang et al., 2019) and carbon productivity (CP) (Hu and Liu, 2016; Wang et al., 2019) as dependent variables in our analysis. Energy efficiency is defined by the ratio of net sales[6] to physical energy consumption[7]. Various types of energies are defined under six major groups: coal, gas, fuel, nuclear, waste, and oil. The average energy efficiency for the Indian manufacturing firm is 0.88. We have estimated emission from the energy consumption data by applying the IPCC's (2006) approach (Chen and Paulino, 2010) as specified in equation (1):

$$C_t = \sum_{k=1}^{6} C_t = \sum_{k=1}^{6} E_{k,t} * NCV_k * CEF_k * COF_k * (44/12) \quad (1)$$

Where, C_t: flow of CO_2 (per 1,00,000kg); $E_{k,t}$: energy consumption forkthinput at period t; NCV_k: The net calorific value of kth input, provided by the IEA Energy Statistics for India (2011); CEF_k: Carbon emission factor for kth input, provided by the National GHG inventories in IPCC (2006); COF_k:The carbon oxidization factor for kth input, normalized to one unit in the calculation; (44/12) is the molecular weight ratio between CO_2 and C.

Finally, we estimate the carbon productivity by taking the net sales ratio to emission. The average carbon productivity for the full sample is 42291.54emissions per output. The covariates are broadly divided into significant factors, such as technological variables (Hu and Liu, 2016; Krugman, 1994; Linn, 2004), policy variables (Moroney, 1992; Pokrovski, 2003; Ren and Hu, 2012), and demand &supply-side factors. We use R&D efficiency, embodied technology import intensity, and disembodied technology import intensity as variables related to technological capabilities at the firm level. Further, total factor productivity is estimated using the semi-parametric technique that takes care of the simultaneity and selectivity bias of the Solow residual (Levinsohn and Petrin, 2003).[8] Firms that continuously reported physical energy consumption data from 1998 to 2019 exhibit an average productivity growth of 4.62 per cent per annum.

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[6]All the monetary variables are deflated using the appropriate deflators taken from the Office of Economic Advisor.

[7]Energy consumption in physical unit is registered in the energy segment of CMIE Prowess. However, the data is unorganized. The data is not also reported in similar or unified units. There differ between the inputs and also within the same input, and for different years. We have cleaned and arranged them under six major categories, and summed them up into aggregate. This data is used for estimating the energy efficiency.

[8]For the construction of capital, we follow (Balakrishnan and Pushpangadan, 1996).

Since a cost-efficient solution suggests complementing technology with price instruments, we incorporate such policy variables in our analysis. We implement two important policy variables, i.e. tax and cap-and-trade, in this study.[9] We have matched the CMIE Prowess and MoEF&CC data to construct firm-level environmental tax (ENVT) and pollution loads indicators. All price instruments are binary, viz. firms under the environmental tax policies are assigned a value of 1, 0 otherwise. Almost 13 percent of firms have implemented environmental tax policy in the sample. The rest of the firms have implemented cap-and-trade, and they are assigned different industrial colour codes based on their pollution loads. For instance, the red category firms are the most polluting, followed by the orange, green, and white categories. Of the sample firms in cap-and-trade, 66 percent belong to the red, 13 per cent to the orange, 4 per cent to the green category, and the rest belong to the white category, respectively. We also use export intensity to represent the demand side and tax rate to define the supply side factor at the firm level.

[9]Environmental tax and colour codes are used as industry dummies to explain the variation of energy efficiency and carbon productivity.

Table 1. Descriptive statistics

Variables	Definition	Observations	Mean	Share (%)
Carbon Productivity (CP)	The ratio between net sales (monetary) and CO_2 emission (physical unit)	1,496	42291.540	
Energy Efficiency (EE.)	The ratio between net sales (monetary) and energy consumption (physical unit)	1,496	0.882	
R&D Efficiency (RE)	The ratio between net sales (monetary) and R&D (monetary)	1,496	1.559	
Embodied Technological Intensity (ETI)	The ratio of expenditure on imported capital on capital goods to net sales (monetary)	1,496	0.009	
Disembodied Technological Intensity (DETI)	The ratio of royalties and technical fee payments in foreign currency (monetary) to net sales(monetary)	1,496	0.001	
Total Factor Productivity Growth (TFPG)	Levinsohn and Petrin (2003)	1,496	4.622	
Export Intensity (EXI)	The ratio between export (monetary) and net sales (monetary)	1,496	0.183	
Tax to Net Sales (TN)	The ratio between tax (monetary) to profit (monetary)	1,496	0.143	
Tax to Profit (TP.)	The ratio between tax (monetary) to net sales (monetary)	1,496	4.435	
Environmental Tax (ET)	If a firm pays environmental tax=1, otherwise 0	1,496		13.235
Red Firms (Red)	If a firm belongs to red industries of MoEF&CC classification=1, otherwise 0	1,496		66.176
Orange Firms (Orange)	If a firm belongs to orange industries of MoEF&CC classification =1, otherwise 0	1,496		13.235
Green Firms (Green)	If a firm belongs to green industries of MoEF&CC classification =1, otherwise 0	1,496		4.411
White Firms (White)	If a firm belongs to white industries of MoEF&CC classification =1, otherwise 0	1,496		16.176

Note: The continuous variables are measured in monetary values (lakhs) at constant prices. Energy consumption and emission are measured in kg (lakhs).

3.2Emission and output growth

There is an argument among different schools of thought over the optimal decision on emission and growth (Lin and Du, 2014). We address the first research question by estimating decoupling growth (Tapio, 2005), using recent empirical literature (Chen et al., 2020; Green, 2021; Sahu and Narayanan, 2010; Yu et al., 2020). We use advanced techniques in assessing decoupling growth to avoid overlapping zone problems. We define decoupling growth as a percentage change in emission (EM) due to the percentage change in aggregate output (Y) as specified in equation (2).

$$\beta_{EM,Y} = (\Delta\, EM/EM)\,/(\Delta Y/Y) \qquad (2)$$

Classification and types of decoupling are presented in table 2. For example, if both EM and Y contract and the contraction of EM surpass the contraction of Y, it is defined as recessive decoupling (RD). Similarly, if the strength of EM contraction is lower, it is referred to as weak negative decoupling (WND). If both of them expand and the expansion of the output is higher, it is referred to as weak decoupling (WD). On the contrary, if the expansion of the output is lower, it is called expansionary negative decoupling (END). If EM contracts and Y expands, it is known as strong decoupling (SD), and if the exact opposite case is found, it is defined as strong negative decoupling (SND). SD is superior to any other outcome, whereas the SND is the worst. WD is better than END as the beta-value of the former is lesser. However, both are superior to RD and WND as the latter two are recessionary situations. Depending on the degrees of contraction, we conclude RD is superior to WND.

Table 2. Definition and types of growth

Growth type	Specification	$(\Delta\, EM/EM)$	$(\Delta Y/Y)$	$\beta_{EM,Y}$
Positive decoupling	RD	<0	<0	$\beta_{EM,Y} > 1$
	WD	>0	>0	$0 < \beta_{EM,Y} < 1$
	SD	<0	>0	$\beta_{EM,Y}<0$
Negative decoupling	END	>0	>0	$\beta_{EM,Y} > 1$
	WND	<0	<0	$0 < \beta_{EM,Y}<1$
	SND	>0	<0	$\beta_{EM,Y} < 0$

Source of classification: Fang and Yu (2021)

We present the year-wise decoupling series in table 3. The result shows that our sample is inconsistent in decoupling over time. For example, 50 percent of the full sample has experienced negative decoupling growth. The best performances are estimated for the following years; 1999, 2009, 2011, and 2016. On the contrary, for 2017 and 2018, the estimated decoupling is weak. Overall, the Indian manufacturing sector has achieved WD, which does not present a best-case scenario for decoupling and needs a better understanding.

Table 3. Year-wise breakdown of growth types for Indian manufacturing sector

Year	$(\Delta EM/EM)$	$(\Delta Y/Y)$	$\beta_{EM,Y}$	Growth type	Specification
1999	-0.04	0.08	-0.47	Positive Decoupling	SD
2000	0.11	0.10	1.08	Negative Decoupling	END
2001	-0.22	-0.04	5.00	Positive Decoupling	RD
2002	0.27	0.06	4.58	Negative Decoupling	END
2003	0.32	0.07	4.76	Negative Decoupling	END
2004	0.37	0.47	0.79	Positive Decoupling	WD
2005	0.15	0.59	0.26	Positive Decoupling	WD
2006	0.30	0.11	2.84	Negative Decoupling	END
2007	-0.16	0.00	31.11	Positive Decoupling	RD
2008	0.14	0.00	34.04	Negative Decoupling	END
2009	-0.03	0.03	-1.02	Positive Decoupling	SD
2010	0.09	0.15	0.62	Positive Decoupling	WD
2011	-0.14	0.06	-2.51	Positive Decoupling	SD
2012	0.22	0.55	0.40	Positive Decoupling	WD
2013	0.01	0.04	0.13	Positive Decoupling	WD
2014	-0.03	-0.03	0.88	Negative Decoupling	WND
2015	-0.03	-0.09	0.32	Negative Decoupling	WND
2016	-0.31	0.01	-39.19	Positive Decoupling	SD
2017	0.18	-0.07	-2.40	Negative Decoupling	SND
2018	0.49	-0.01	-39.74	Negative Decoupling	SND
2019	-0.95	-0.09	10.73	Positive Decoupling	RD
Overall	0.03	0.09	0.38	Positive Decoupling	WD.

Note: Authors' estimation; beta value is the ratio of the mean value of change in emission and change in output.

Along with the earlier decoupling results, we also estimate decoupling at industry levels and present it in table 4. Industries such as coke and refined products, computers, electronics and allied, pharmaceutical, and textile industries perform best in decoupling growth. In comparison, woods and wood products have performed the worst.

Table 4. Industry-wise decoupling growth

Industry	$(\Delta EM/EM)$	$(\Delta Y/Y)$	$\beta_{EM,Y}$	Growth type	Specification
Basic metal	0.04	0.09	0.48	Positive Decoupling	WD.
Chemical and chemical products	0.03	0.08	0.36	Positive Decoupling	WD.
Coke and refined products	-0.14	0.20	-0.71	Positive Decoupling	SD
Computer, electronics and allied	-0.09	0.13	-0.71	Positive Decoupling	SD
Electrical equipment	0.14	0.07	1.87	Negative Decoupling	END
Fabricated metal	0.18	0.10	1.75	Negative Decoupling	END
Food products	0.12	0.09	1.36	Negative Decoupling	END
Machinery and equipment	0.02	0.16	0.12	Positive Decoupling	WD.
Motor vehicles	0.11	0.06	1.75	Negative Decoupling	END
Other non-metallic products	0.08	0.09	0.80	Positive Decoupling	WD.
Paper and paper products	0.03	0.14	0.20	Positive Decoupling	WD
Pharmaceuticals	-0.11	0.05	-2.24	Positive Decoupling	SD
Rubber and plastic	0.10	0.09	1.09	Negative Decoupling	END
Textile	-0.02	0.07	-0.31	Positive Decoupling	SD
Wearing apparel	0.09	0.08	1.10	Negative Decoupling	END
Wholesale trade	0.01	0.04	0.26	Positive Decoupling	WD.
Wood and wood products	0.13	-0.01	-13.45	Negative Decoupling	SND

Note: Authors' estimation

3.3 Technological capabilities and emissions

One of the major concerns is finding plausible reasons for the underperformance in decoupling growth in India's manufacturing sector. Since India's manufacturing industry represents a case of weak decoupling growth, absolute emission control should be considered. In this context, decomposition literature helps examine the drivers of emission control for India's manufacturing sector.

Further, decomposition analysis will help us check technological advancement and industrial activities on emission control (Kaya, 1989). We use the extended Log Mean Divisia Index (LMDI) (Wang and Feng, 2018).[10] We define aggregate emission as the sum of emissions from all energy inputs consumed at a firm level. In equation (3), this is further divided into several factors: (1) Pollution intensity (PI): ratio of emission to energy consumption; (2) Energy mix (EMIX): ratio of consumption of specific energy input by a firm to its total energy consumption; (3) energy intensity (ECQ): ratio of energy consumption to net sales; (4) R&D efficiency (RE): ratio of net sales to R&D; (5) R&D intensity (RI): ratio of R&D to net sales; (6) investment intensity (II): ratio of investment[11] to net sales; and (7) industrial activities (Q): defined by the net sales of a firm.

$$EM^t = \sum_{i=1}^{68}\sum_{j=1}^{6} EM_{ij}^t = \sum_{i=1}^{68}\sum_{j=1}^{6} \frac{EM_{ij}^t}{EC_{ij}^t} * \frac{EC_{ij}^t}{EC_i^t} * \frac{EC_{ij}^t}{Q_i^t} * \frac{Q_i^t}{R_i^t} * \frac{R_i^t}{I_i^t} * \frac{I_i^t}{Q_i^t} * Q_i^t$$

$$= \sum_{i=1}^{68}\sum_{j=1}^{6} EMPI_{ij}^t * EMEMIX_{ij}^t * EMECQ_i^t * EMRE_i^t * EMRI_i^t * EMII_i^t * EMQ_i^t \qquad (3)$$

Where t represents year; i represents the firms, and j describes the energy sources; $EMPI_{ij}^t$: Pollution intensity of the i^{th} firm from the j^{th} fuel at period t; $EMEMIX_{ij}^t$: Energy mix of the i^{th} firm from the j^{th} fuel at period t; $EMECQ_i^t$: Energy intensity of the i^{th} firm at period t; $EMRE_i^t$: R&D efficiency of the i^{th} firm at period t; $EMRI_i^t$: R&D intensity of the i^{th} firm at period t; $EMII_i^t$: Investment intensity of the i^{th} firm at period t; EMQ_i^t: Industrial activities of the i^{th} firm at period t.

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[10]A similar idea of provinces is applied to the firm level analysis.

[11]We have estimated the difference between the capital stock of consecutive two periods to calculate the investment of a firm.

The change in aggregate emission is the difference between two consecutive periods. This difference arises from the changes in the composition of different components specified in equation (4). Hence, following (Wang et al., 2017) we can modify the preceding equation and specify as:

$$\Delta EMAGG = EMAGG^{t} - EMAGG^{t-1} = \Delta EMPI + \Delta EMEIX + \Delta EMECQ + \Delta EMRE + \Delta EMRI + \Delta EMII + \Delta EMQ \quad (4)$$

$\Delta EMPI$: emission from an additional unit of energy consumption; $\Delta EMEIX$: emission from an additional source of specific energy in the total energy used; $\Delta EMECQ$: emission from an extra unit increase in energy intensity; $\Delta EMRE$: emission generated from an additional unit of increase in technological efficiency; $\Delta EMRI$: emission from an additional unit increase in R&D intensity; $\Delta EMII$: emission from an additional unit increase in investment intensity; ΔEMQ: emission from an additional unit increase in industrial sales.

Accordingly, these factors are estimated using equations (5) to (11):

$$\Delta EMPI = \sum_i \frac{EMAGG_{ij}^{t} - EMAGG_{ij}^{t-1}}{\ln EMAGG_{ij}^{t} - \ln EMAGG_{ij}^{t-1}} \left(\ln EMPI_{ij}^{t} - \ln EMPI_{ij}^{t-1}\right) \quad (5)$$

$$\Delta EMEMIX = \sum_i \frac{EMAGG_{ij}^{t} - EMAGG_{ij}^{t-1}}{\ln EMAGG_{ij}^{t} - \ln EMAGG_{ij}^{t-1}} \left(\ln EMEMIX_{ij}^{t} - \ln EMEMIX_{ij}^{t-1}\right) \quad (6)$$

$$\Delta EMECQ = \sum_i \frac{EMAGG_{ij}^{t} - EMAGG_{ij}^{t-1}}{\ln EMAGG_{ij}^{t} - \ln EMAGG_{ij}^{t-1}} \left(\ln EMECQ_{ij}^{t} - \ln EMECQ_{ij}^{t-1}\right) \quad (7)$$

$$\Delta EMRE = \sum_i \frac{EMAGG_{ij}^{t} - EMAGG_{ij}^{t-1}}{\ln EMAGG_{ij}^{t} - \ln EMAGG_{ij}^{t-1}} \left(\ln EMRE_{ij}^{t} - \ln EMRE_{ij}^{t-1}\right) \quad (8)$$

$$\Delta EMRI = \sum_i \frac{EMAGG_{ij}^{t} - EMAGG_{ij}^{t-1}}{\ln EMAGG_{ij}^{t} - \ln EMAGG_{ij}^{t-1}} \left(\ln EMRI_{ij}^{t} - \ln EMRI_{ij}^{t-1}\right) \quad (9)$$

$$\Delta EMII = \sum_i \frac{EMAGG_{ij}^{t} - EMAGG_{ij}^{t-1}}{\ln EMAGG_{ij}^{t} - \ln EMAGG_{ij}^{t-1}} \left(\ln EMII_{ij}^{t} - \ln EMII_{ij}^{t-1}\right) \quad (10)$$

$$\Delta EMQ = \sum_i \frac{EMAGG_{ij}^{t} - EMAGG_{ij}^{t-1}}{\ln EMAGG_{ij}^{t} - \ln EMAGG_{ij}^{t-1}} \left(\ln EMQ_{ij}^{t} - \ln EMQ_{ij}^{t-1}\right) \quad (11)$$

Table 5 shows the year-wise estimates of the decomposition from the extended LMDI approach for 68 Indian manufacturing firms.[12] Using this approach, we can explain a reduction of 34.6 Mt[13] of emission for sample firms. Expenditure on research and development (RE) is the most significant driving force to stimulate emission, as we hypothesized, and followed by Q, ECQ, PI, II, RI, and EMIX. The implications are analogous to recent studies (Wang and Feng, 2018). Hence, we conclude RE helps improve carbon productivity but at the cost of increasing the absolute emission. Therefore, by setting an optimal emission limit, R&D efficiency can also be limited to a certain extent. This would help balance between the investment of output and emission decisions. Therefore, the climate policy of India's manufacturing sector should not only focus on increasing carbon productivity, but also to reduce absolute emissions to match with the international policy goals in mitigating emissions from the high emitting sectors.

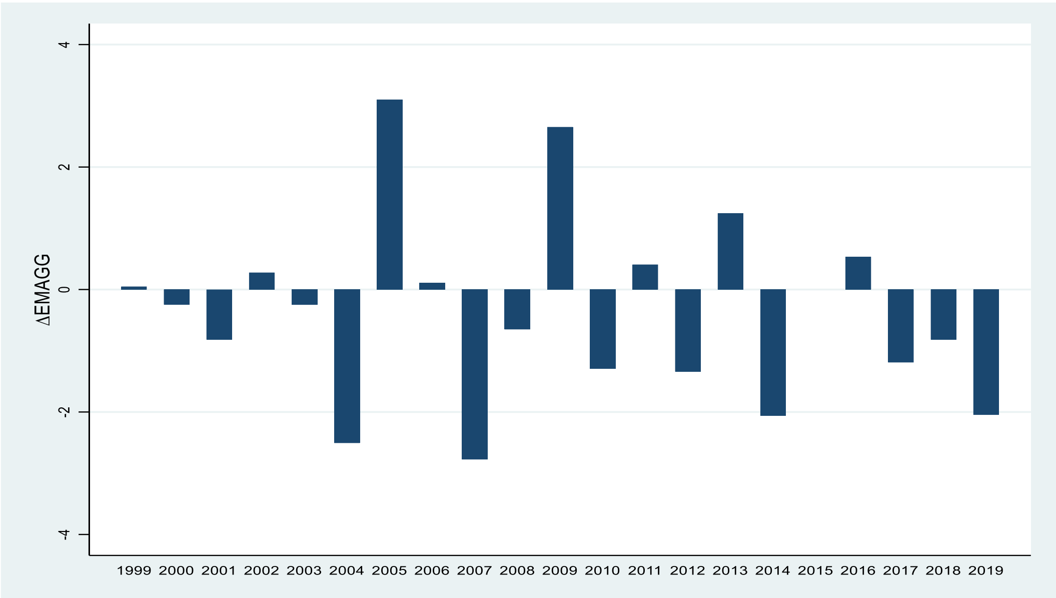
The mean aggregate change in emission per annum is presented in figure 1. It exhibits fluctuations throughout the sample. The distribution ranges from -277.5 Mt to +310.2 Mt. There are two major increases in emissions reported from 2004 to 2005 and 2008 to 2009. The first increase has happened due to increased industrial activities/production (see table 5). The increase in the second period is due to several factors at firm level and can be identified as movement in PI, EMIX, RE, II, and Q. In addition, these firm-level factors are also associated with the financial crisis. Due to the recession, imports have reduced from the import dependent/advanced economies, and hence a negative effect on technology upgradation and heavy dependence on the dirty fuel for production process. To fill this gap new investments have injected in the Indian economy. However, the investments have not directed to focus on cleaner fuels or technology related to energy and carbon efficiency gain. This is one of the reasons of the statistical relationship between R&D intensity and emission, (a positive influence). Therefore, to ensure the emission control and improvement in carbon productivity R&D efficiency has to be backed by R&D intensity. This means not only a higher portion of income should be invested but also a higher proportion of that investment has to be invested on R&D directed towards green technologies. It may help the industries to

[12]Some values are missing in the 6th and 7th column because of the negative investment values that are dropped out after the necessary adjustments.
[13]The bottom right cell shows the value is -0.346; it is measured in kg (lakhs). We have transferred it to Mt.

control the threat of rebound generated from R&D efficiency, especially during the phases such as post-recession. However, we also need to ensure whether this emission control is translated to ensure better carbon productivity or not.

Other than these factors, the policy implementation has also influenced emission from this sector. Emission has increased for the year 2013 and 2016. Higher energy intensity, energy mix, and R&D intensity are the main drivers for inducing emissions in 2013. This has mainly happened due to the Performance, Achievement, and Trade (PAT)-I policy. Initially, firms bought the permit and emitted more. However, technological investment and the strategic business adjustment produced positive results in the following years. A similar case is also found during the implementation of PAT-II. Along with the previous factors, increase in the net industrial sales also increased emission for the year 2016. The successive rapid incidents have led to a fluctuation of the change in emission in the manufacturing sector of Indian economy.

Figure 1. Change in aggregate emission (absolute)



Note: Authors' calculation; the bars represent the average of the change in emission per annum in kg (lakhs)

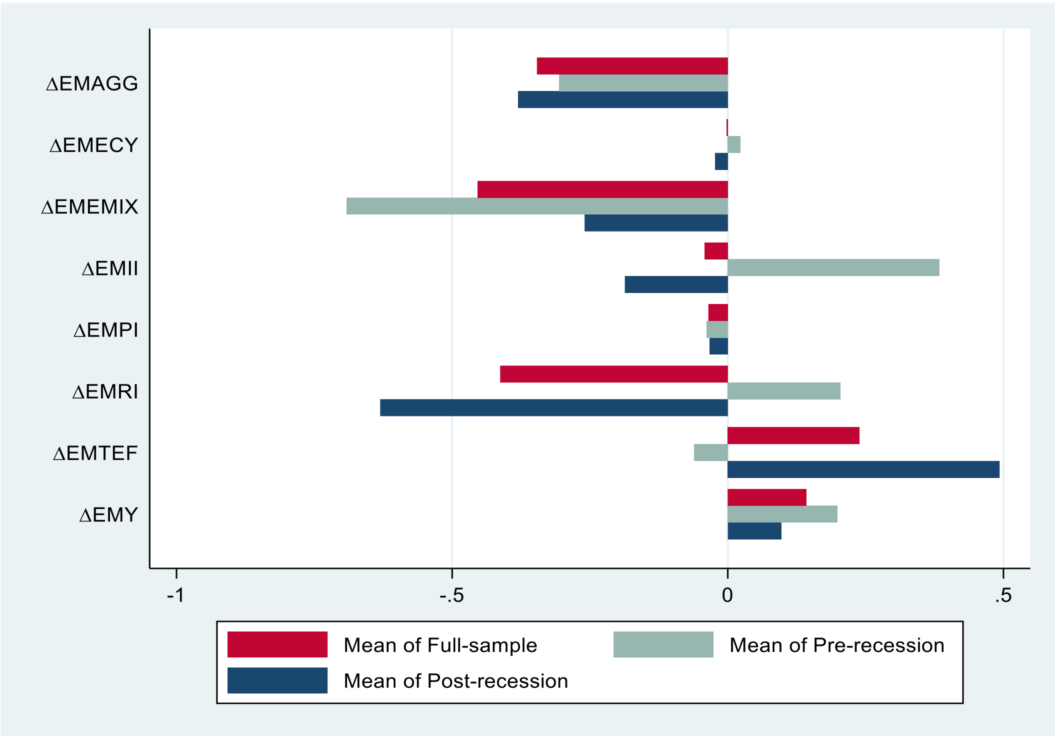
Table 5. Year-wise decomposition of extended LMDI

Year	ΔEMPI	ΔEMEMIX	ΔEMECQ	ΔEMRE	ΔEMRI	ΔEMII	ΔEMQ	ΔEMAGG
1999	0.005	0.110	-0.054	-0.149	-	-	0.036	0.049
2000	-0.034	-0.235	0.146	0.091	0.508	-0.350	0.026	-0.246
2001	-0.052	-0.522	-0.361	0.152	-	-	0.070	-0.816
2002	0.070	-0.013	0.119	0.528	-	-	-0.035	0.277
2003	-0.033	-0.760	0.405	-0.015	-	-	0.138	-0.250
2004	0.090	-3.356	0.257	0.211	-	-	0.447	-2.507
2005	0.063	-0.204	-0.426	0.148	-4.696	4.544	0.736	3.102
2006	0.008	-0.310	0.310	-0.802	1.335	-0.321	0.267	0.108
2007	-0.464	-0.800	-0.206	-0.768	4.581	-2.479	0.085	-2.775
2008	-0.190	-1.808	0.532	0.206	-1.942	1.218	0.045	-0.651
2009	0.032	1.333	0.394	0.533	-4.674	1.951	0.098	2.654
2010	-0.213	-1.002	0.233	-0.025	1.216	-0.719	0.066	-1.293
2011	0.057	0.216	-0.156	0.799	-2.701	0.818	0.058	0.408
2012	-0.011	-0.164	-0.901	1.081	0.494	-1.640	0.879	-1.341
2013	-0.027	1.523	0.047	-0.269	0.619	-0.427	0.059	1.245
2014	0.035	0.025	-0.024	0.062	2.733	-2.782	-0.097	-2.061
2015	-0.001	0.038	-0.036	-0.016	-0.029	0.045	-0.005	0.000
2016	-0.030	1.085	-0.599	-0.099	0.009	0.117	-0.007	0.534
2017	-0.215	-2.975	1.348	1.038	-1.997	0.811	0.019	-1.191
2018	0.014	-0.546	0.590	2.147	-0.050	-1.406	0.027	-0.818
2019	0.197	-0.633	-1.785	-0.039	-0.140	0.144	-0.085	-2.047
Overall	-0.035	-0.454	-0.002	0.239	-0.413	-0.042	0.143	-0.346

Note: Authors' calculation; all the values are reported in kg (lakhs).

Since R&D efficiency, emission control, and carbon productivity has a puzzle, we further divide our sample into two sub-samples, pre-recession (up to 2007) and post-recession (2008 and onwards) for further analysis. Figure 2 explains similar results as in table 5. RE has initially helped reduce the emission in pre-recession, but there is a rebound in the post-recession that led to higher emissions. Further, RI and EMIX have contributed to emission reduction; however, EMIX has performed better in the pre-recession period. Additionally, the contraction in RI is estimated for the post-recession period, which helped in reducing emissions.

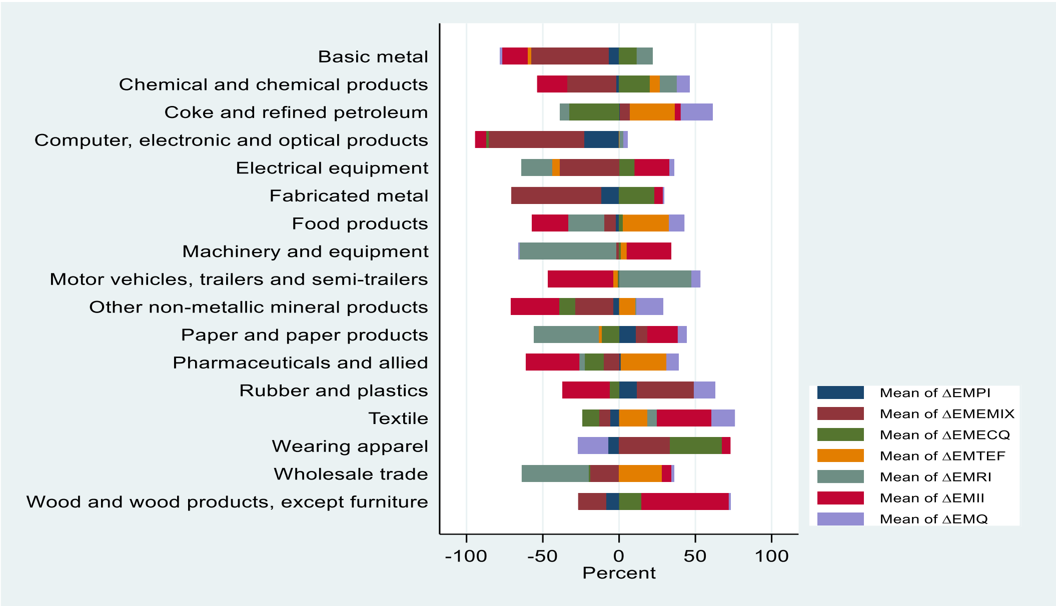
Figure 2. Contribution of various components on the emission growth



Note: Authors' estimation; the red bars denote full sample, the grey bars represent pre-recession, and blue bars signify the post-recession.

We further analyze the industry-level decompositions in figure 3. The result explains a heterogeneous effect for each industry. For example, EMIX has helped in emission reduction for the sectors such as basic metal, chemical, computers and allied, electrical equipment, fabricated metal, pharmaceutical, wholesale trade, and wood products. However, it has stimulated the emission of the rubber and plastics segments of India's manufacturing sector. On the contrary, RE has induced the emission in coke, food, pharmaceutical, the textile sector. ECQ has caused emissions in industries such as chemical, fabricated metal, wearing apparel, and wood. RI has induced the emission for motor vehicles and reduced the emission in food, machinery, papers etc. Similarly, investment intensity and industrial activities have also heterogeneous impacts across the industries.

Figure 3. Industry-wise break-up of emission growth components



Note: Authors' calculation

3.4 The threshold regression models

Since literature on R&D efficiency is directly linked with improvement in carbon productivity, we need to further examine for the manufacturing sector in India and see the outcomes. A direct link between R&D efficiency and carbon productivity will help control emission and improve carbon productivity simultaneously. Our initial results indicate a scope to examine possible solutions to improve the decoupling growth for India's manufacturing sector. Therefore, we focus on the empirical analysis of the optimal trade-off between emission and output growth. We are not able to use the modified decomposition techniques as (1) missing values in the sample, (2) high correlation between variables, and (3) difficult to address the price effect.

However, EE and CP can be explained by the firm characteristics, such as technological capabilities, demand and supply-side factors and policy variables. Hence, we apply threshold regression to address our second research question. This will help us to capture the impact of RE on CP for different thresholds. This is important because if the effects for different thresholds vary, ordinary regression will give a biased estimation as the distribution becomes non-standard because of "*nuisance parameter problem*". Hence, we construct our regression equation that determines the level of sustainability of the CP for different levels of R&D efficiency, as presented in equations (12) and (13) (Fang and Yu, 2021; Hansen, 1999).

$$lnEE_{it} = \beta_0 + \beta_1 L.EE_i t.I(lnRE \leq \gamma_1) + \beta_2 L.EE_i t.I(lnRE > \gamma_1) + \beta_k Z_{it} + \varepsilon_{it} + \mu_i \tag{12}$$

$$lnCP_{it} = \beta_0 + \beta_1 L.CP_i t.I(lnRE \leq \gamma_1) + \beta_2 L.CP_i t.I(lnRE > \gamma_1) + \beta_k lnZ_{it} + \varepsilon_{it} + \mu_i \tag{13}$$

For both the models, *I* and *t* represent the firm and year, respectively. These models will capture multiple breaks with the help of the indicative function I(.), and it takes the value one if the terms in the parenthesis are true, otherwise 0. γ represents the threshold value, and β denotes the parameter, and they are estimated using the non-linear least square method. Further, we estimate the level of significance for the thresholds and the authenticity tests. A "self-sampling method" is proposed for robust results (Hansen, 1999). This follows an asymptotic distribution of the F-statistic and helps to construct the p-values for significance tests. The second test helps in constructing the confidence intervals for the threshold values as per the given value of the LR-statistics, and the condition is $LR(\gamma_0) \leq -2\ln\left(1 - \sqrt{1-\alpha}\right)$ where α is the level of significance. Z is the vector of the control variables, i.e. EXI, TN, TP, TFP, ETI, and DETI.[14] ε_{it} is the random interference term and $\mu_i$denotes the individual specific effect.

4. The empirical findings

We explain factors that explain carbon productivity and energy efficiency. The correlation between is presented in table A-1 in the appendix. Since EE and CP are highly correlated, we

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[14]The variables are taken in the logarithm.

estimate them separately. If the factors affecting EE are the same as in the case of CP, we conclude that achieving energy efficiency can act as a proxy for emission reduction, which helps in designing direct policy for the manufacturing sector targeting the energy efficiency. As we have balanced panel data, we first estimated the panel unit root tests. The results are presented in table A-2 in the appendix. From the results obtained, we reject the null hypothesis and confirm that panels are stationary. This can also explain the stability of our variables. However, unit root tests do not validate the long-run stability of variables, and hence we use the cointegration test before estimating our empirical equations (12) and (13). We confirm that the series are cointegrated from the cointegration test and stable for long-run analysis. Results of the cointegration tests are presented in table A-3 of the appendix. We also conducted a multicollinearity test for each dependent variable of interest further and reported in table A-4 in the appendix. Since the variance inflation factor (VIF) is less than 10, we conclude that the issue of multicollinearity is absent in our series of variables. Our empirical analyses are classified into three sub-sections. Firstly, we present determinants of energy efficiency and carbon productivity. Secondly, we arrive at the inter-firm heterogeneity, and lastly, we explain the factors explaining different club-convergence.

4.1 Determinants of energy efficiency and carbon productivity

We present the estimated coefficients of the regression results in table 6. Model (1) and (2) determine the influence of covariates on EE. The rest of the models explain the case of CP Model (1) is the single threshold regression, and model (2) is the double threshold regression for EE In model (1), we find that R&D efficiency helps to induce the EE. The first threshold level is specified in table 6, and it is -0.02, which is 0.98 in absolute terms. Therefore, we conclude that lag EE helps increase the current EE if the RE is below 0.98. Once it exceeds the threshold level, it stimulates EE with lower impact. However, based on the p-value of table 6, we reject the double threshold estimate for the EE. The acceptance of the first threshold model is shown in figure-4.[15] Our results also confirm that other than RE, export intensity, tax on net profit, embodied technology import intensity, and productivity also

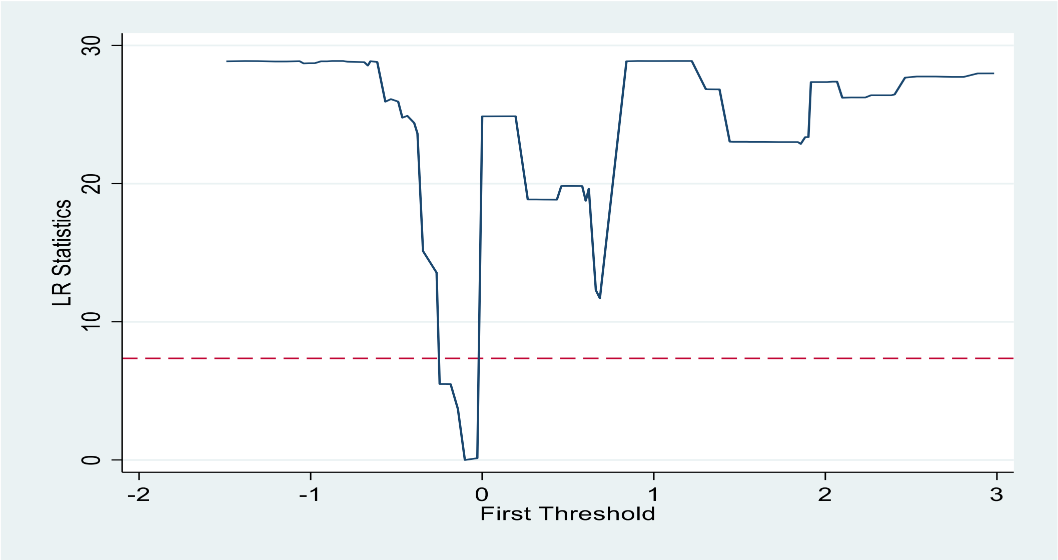
[15]The red dot lines in figure 1 and 2 are the confidence interval specified by Hansen at 5 per cent level of significance. The vertical axis measures the LR-statistics and the horizontal axis measures the threshold range.

explain EE at the firm level. These results confirm that the demand and supply-side factors are related to EE at the firm level other than technological capabilities. The industry level dummies have two major implications: i. the environmental tax reduces the energy efficiency of the firms. This may happen because either the polluter may choose to pollute and pay, or there is a rebound effect (Bagchi and Sahu, 2020; Chakravarty et al., 2013); ii. Since red firms are found to be energy-intensive and, orange firms are energy efficient, and we conclude that polluting firms are energy-intensive.

We also conduct the authenticity for EE, which is presented in table 6. The results show that the threshold estimates fall at 95 percent confidence level, and the range lies between -0.18 to 0.00, which is 0.83 to 1 in absolute value. This confirms that firms that have R&D efficiency are energy efficient and sustainable. We carry out a similar analysis for CP in models (3-4). From the threshold specification presented in table 6, we select model (3) as the efficient model as the double threshold is rejected (figure-5). Results indicate that lag CP is most effective if the RE is below -0.10, i.e. 0.90 in absolute value. The impact of sustainability reduces if RE crosses this threshold. This implies that R&D efficient firms are carbon productive. The authenticity tests suggest that the first threshold lies between -0.16 to -0.02, which is 0.85 and 0.98 in absolute terms. The other set of vectors that influence the CP are similar to EE, except for tax on net sales. This implies that technological capabilities and demand factors influence CP. We find similarities in results for both EE and CP in our empirical estimates. Hence, we conclude that energy efficiency is a good policy proxy for carbon productivity, i.e. effective energy policy complements climate change mitigation.

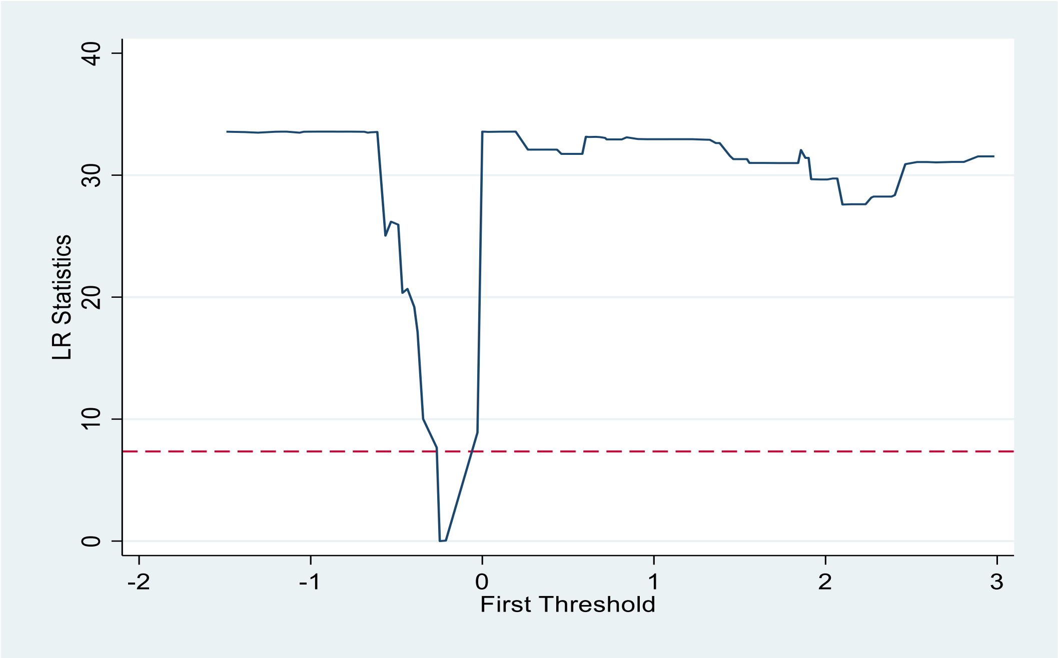
The analysis is helpful in terms of strategizing the emission control policy. However, not all the firms exhibit similar emission patterns. Hence, we need to address the heterogeneity of the firms in terms of emission so that we can prescribe the exact policies for different firms. This is analyzed in the following section with a convergence analysis that will address the final research question.

Figure 4. The first threshold for energy efficiency



Note: Authors' estimation

Figure 5. Different thresholds for carbon productivity



Note: Authors' estimation

Table 6. Determinants of energy efficiency and carbon productivity

Explanatory Variables	Energy Efficiency		Carbon Productivity	
	(1)	(2)	(3)	(4)
lnEXI	1.352***	1.422***	1.286***	1.347***
	(0.524)	(0.522)	(0.408)	(0.406)
lnETI	0.0481	0.048	0.076***	0.0677***
	(0.032)	(0.032)	(0.025)	(0.025)
lnDETI	-0.047	-0.045	-0.095**	-0.064
	(0.061)	(0.061)	(0.048)	(0.048)
lnTFP	0.324***	0.334***	0.360***	0.357***
	(0.107)	(0.107)	(0.083)	(0.082)
lnTN	0.241**	0.237*	0.045	0.025
	(0.122)	(0.122)	(0.095)	(0.094)
lnTN	0.069	0.0667	0.085	0.081
	(0.103)	(0.102)	(0.079)	(0.079)
lnET	-0.190***	-0.187***	-0.089***	-0.091***
	(0.033)	(0.033)	(0.0262)	(0.026)
lnRed	0.070***	0.064***	0.069***	0.062***
	(0.017)	(0.017)	(0.013)	(0.013)
lnOrange	-0.062*	-0.062*	-0.043*	-0.047*
	(0.033)	(0.033)	(0.026)	(0.026)
lnGreen	0.043	0.0341	0.043	0.012
	(0.055)	(0.055)	(0.043)	(0.043)
lnRE-1	4.661***	5.008***	0.0001***	0.0001***
	(0.805)	(0.811)	(2.03e-05)	(1.99e-05)
lnRE-21	0.019***	0.612***	4.27e-07***	3.89e-05***
	(0.005)	(0.204)	(1.42e-07)	(7.88e-06)
lnRE-22		0.019***		4.20e-07***
		(0.005)		(1.41e-07)
Constant	-37.81	-30.39	-57.74**	-44.22*
	(30.59)	(30.62)	(23.79)	(23.84)
Observations	1,428	1,428	1,428	1,428
Number of id	68	68	68	68
R-squared	0.103	0.111	0.141	0.150
Sigma_u	184.906	178.923	122.88	118.302
Sigma_e	2.613	2.602	2.033	2.022
Rho	0.999	0.999	0.999	0.999
R-Square: Within	0.102	0.110	0.140	0.150
R-Square: Between	0.004	0.004	0.008	0.010
R-Square: Overall	0.003	0.003	0.006	0.007
F-value	12.88***	12.92***	18.38***	18.35***
F test that all u_i=0	60.66***	51.59***	47.12***	41.08***

Note: Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7. Selection of threshold

Threshold Variable	Model	F-value	P-value	1%	5%	10%	Threshold estimates	95% Confidence Interval
lnEE	Single threshold	38.75	0.000	32.51	25.60	19.15	-0.02	[-0.18, 0.00]
	Double threshold	8.68	0.346	31.74	24.65	21.02	-0.10	[-0.20, -0.02]
							0.90	[0.34, 0.96]
lnCP	Single threshold	70.72	0.000	45.33	24.60	19.73	-0.10	[-0.16, -0.02]
	Double threshold	16.25	0.166	41.68	24.43	19.75	-0.24	[-0.26, -0.21]
							0.00	[-0.18, 0.03]

Note: Authors' estimation

4.2 Inter-firm heterogeneity

Following (Kim, 2015; Mohammadi and Ram, 2012; Yu et al., 2015), we estimate the inter-firm heterogeneity in carbon productivity. One way to address the problem is to estimate club convergence (Brannlund et al., 2015; Dong et al., 2013; Green 2021). Studies have addressed club convergence for carbon productivity (Apergis and Payne, 2017; Burnett, 2016; Parker and Liddle, 2017; Zhang and Broadstock, 2016). We apply one of the recent techniques to estimate club convergence (Phillips and Sul, 2007). The basic idea is that similar firms will club together and approach different equilibrium or convergent paths instead of a unique equilibrium. The estimation technique helps us to capture both the cross-section and time-series heterogeneity within panels.

First, we rank firms on carbon productivity (most recent year). Next, we choose k highest ordered firms to form the sub-group where k lies between 2to N. After running log(t) regression, the convergence statistic for the sub-group is estimated where $t_k = t(G_k)$. To choose the group size k^* t-statistic ranked by maximizing over k where $k^* = \arg\max[t_k]$ subject to min $t_k > -1.65$.[16] If the constraint is not satisfied, the highest carbon productive firms are dropped from the sub-group, and a new group is formed. This process is continued until we create the core group. Once the core group is specified, Phillips and Sul (PS) regression are re-estimated. If t_k exceeds the critical value of PS, it is included in the new convergent group and added to the core group. The groups that are not added to the first convergent group are dropped out and grouped into the subsequent clubs. These steps are continued until all convergent clubs are formed, and the remaining firms are clubbed into the divergent group.

The final clubs are represented in table 8. The numbers in the column of the 'firms' denote the rank of the firms based on the CP. Table 8 describes the initial groups into six categories, and out of them, one club is divergent. We also observe that firms come in different clubs, even classified in the same industry. All the convergent clubs have higher t-statistics than -1.65, except the divergent group. The t-statistics suggests that the 6th club is only divergent. Out of all the clubs, 31per cent belongs to club-1; 12 per cent belongs to club-2; 25 per cent

[16]A detailed analysis is carried out by Bai et al. (2019) and Bhattacharya et al. (2018) regarding the construction of the t-statistics.

belongs to club-3; 15 per cent belongs to club-4; 7 per cent belongs to club-5, and the rest are divergent groups. Half of the beta coefficients values denote the speed of the convergence. We conclude that the 4thclub converges fastest, and the 5th club is the slowest in terms of convergence. Since the beta value is less than 2, it rejects the null hypothesis of absolute convergence, and hence we conclude it exhibits a relative convergence.

We look into the decoupling pattern of every club. Table 9 represents the ranks of the clubs based on their CP. Our finding suggests that only club-1 exhibits a strong decoupling. On the contrary, club-5 has negative decoupling and rank 3rd in carbon productivity. Hence, there is a scope for improvement. The study addresses the heterogeneity of the firms in terms of carbon productivity. We find five major groups exhibit different characteristics. Hence, a unique policy for all the groups will not be ideal; instead, we conclude that separate policy suggestions are required for different groups. Hence, we determine the factors influencing the choice of the club in the following section.

Table 8. Final clubs of firms

Clubs	Firm IDs	No. of firms	Frequency	Percent	Status	b-coefficient	t-statistic
Aggregate						-0.64	-17.91
1	51, 36, 41, 8, 47, 31, 24, 66, 63, 59, 60, 54, 55, 64, 56, 49, 48, 62, 61, 65, 57	21	462	30.88	Convergent	-0.04	-1.42
2	22, 53, 50, 52, 45, 40, 44, 46	8	176	11.76	Convergent	-0.16	-1.32
3	6, 43, 34, 20, 25, 35, 5, 30, 32, 10, 27, 23, 39, 37, 38, 29, 33	17	374	25.00	Convergent	-0.18	-1.51
4	17, 21, 15, 18, 16¸ 11, 9, 3, 28, 7	10	220	14.70	Convergent	2.25	6.36
5	12, 26, 13, 19, 4	5	110	7.35	Convergent	-0.62	-0.82
6	42, 14, 67, 68, 1, 58, 2	7	154	10.29	Divergent	-0.68	-29.81

Note: Authors' estimation; the speed of convergence is predicted from the beta coefficient.

Table 9. The growth pattern of different clubs

Club	Rank	CP	$(\Delta EM/EM)$	$(\Delta Y/Y)$	$\beta_{EM,Y}$	Growth type	Specification
1	1	7248.25	-0.03	0.09	-0.32	Decoupling	SD
2	2	4745.35	0.02	0.10	0.24	Decoupling	WD
3	4	866.36	0.05	0.09	0.59	Decoupling	WD
4	5	40.90	0.02	0.09	0.19	Decoupling	WD
5	3	1410.34	0.27	0.04	6.88	Negative decoupling	END

Note: Authors' estimation.

4.3 Factors influencing different clubs

The club convergence estimates the heterogeneity of the inter-firm variation. We focus on carbon productivity in understanding club convergence. However, other economic factors can influence the choice of clubbing. We try to capture the influence of these factors using equation (14).

$$\Pr(Club_{it} = 1) = \phi(\alpha + \beta CP_{i,t} + \boldsymbol{Z} + \mu_{ij,t}) \qquad (14)$$

Whereϕ represents the standard normal cumulative distribution, and the control variables are denoted as $\boldsymbol{Z}$ that also accounts for the time and firm-specific effects. The subscript *i* indicates the firm specification and *t* represents the time. The data is binary, and it takes a value one if it belongs to the corresponding group, otherwise 0.

The main variable of interest is carbon productivity. However, the model can suffer from the issue of endogeneity. This is because the firms' form the clubs based on ranks of the latest year's carbon productivity. To omit this issue, we introduce the IV Probit, where CP is treated as endogenous, and it depends on a variable other than the variables specified in $\boldsymbol{Z}$ vector. This particular variable should be exogenous to the system, and the model is assumedrecursive, i.e. CP enters into equation (14) but the clubs do not enter into the CP's equation. Both the error terms follow a normal distribution (N~0, ∑). The rule of thumb is ∑ cannot be a block diagonal between the two error terms. Otherwise, CP would not be endogenous. In our model, we introduce lag of carbon productivity. Studies find that Indian manufacturing sector's energy management and emission control is endogenous its own lag (Bagchi and Sahu 2020; Sahu et al., 2021; Sahu and Mehta, 2018; Sahu and Narayanan, 2014).

We present the marginal effects in table 10 for five consecutive clubs in models (5) to (9). The Wald test for exogeneity throughout all the models suggests that IV Probit would be suitable for taking care of the endogeneity. Our estimation suggests that the instrument is not weak and it is exogeneous to the model.[17] Model (5) indicates that new firms with higher lag

[17]First-stage estimation of IV Probit is given in the appendix (table A-5).

CP tend to move to club-1 through an improvement of current CP. This suggests that carbon productive firms ensure better decoupling growth, or alternatively, a carbon intensive firm performs poorly in terms of decoupling growth. Hence, improvement in carbon productivity becomes the thumb rule for future sustainability in terms of decoupling growth. Higher export intensity induces the firms to move out from club-1, i.e., export-intensive are not focusing on long term convergence path of sustainability. Hence, a sustainable export promotion policy is urgently required to ensure better decoupling for the export intensive firms. In addition, higher environmental tax induces the firm's probability to move out from club-1.A similar analysis also holds for the cap-and-trade. In model (6), we observe a similar finding for CP.

However, export intensive firms[18] increase the probability for the firms to move into the club-2 category. A higher corporate tax or a higher environmental tax induces the probability of the firms to choose club-2. On the contrary, the most polluted firms (red) try to move into club-2. In addition to that, the technological factors, viz. RE and DETI exhibit positive influences. Model (7) estimates the probability of moving in club-3 due to several explanatory factors. A higher CP produces an opposite result with the previous findings for the choice of rest of the clubs. This is in line with the previous argument of CP and clubbing. The supply-side factors (TP) and productivity negatively influence the choice of clubbing.

In model (8), we estimate the determinants of club-4. EXI, RE, and polluting firms negatively affect club-4; whereas, TP, ETI, DETI have positive impact. The positive influence of embodied and disembodied technologies may be one of the reasons for this group to be the fastest convergent. Model (9) gives us the estimate of the convergence for club-5. We observe a positive influence of EXI, TN, DETI, TFP, and the colour codes. The negative influence of CP makes club-5 the slowest converging club.

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[18]In few of the regressions from model (6) and onwards, some variables are dropped out because of the multicollinearity.

Table 10. Factors explaining the convergence of the manufacturing firms

Explanatory Variables	Marginal Effects				
	(5)	(6)	(7)	(8)	(9)
lnCP	0.20***	0.22***	-0.09***	-0.32***	-0.17***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
lnEXI	-0.05**	0.19***	0.007	-0.11***	0.08**
	(0.02)	(0.04)	(0.02)	(0.03)	(0.03)
lnTN	0.08	0.10*	-0.18***	-0.11	0.30***
	(0.05)	(0.06)	(0.05)	(0.08)	(0.06)
lnTP	0.005	0.16***	-0.19***	0.23***	-0.004
	(0.04)	(0.06)	(0.06)	(0.06)	(0.06)
lnETI	-0.009	-0.01	0.004	0.04**	-0.02
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
lnDETI	0.02	0.08***	-0.08***	0.15***	0.09***
	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)
lnRE	-0.02	0.18***	-0.20***	-0.27***	0.32***
	(0.05)	(0.05)	(0.05)	(0.07)	(0.06)
lnTFP	0.008	0.02	-0.14***	0.05	0.31***
	(0.03)	(0.04)	(0.03)	(0.05)	(0.07)
ET	-0.0006***	0.001***	0.01	-	0.001***
	(0.0001)	(0.0001)	(0.007)		(0.0001)
Red	-0.0005***	0.0001***	0.01*	-0.0003***	0.0006***
	(0.00009)	(0.00007)	(0.007)	(0.00008)	(0.00009)
Orange	-0.0002**	-	0.01	-0.0009	0.0009***
	(0.0001)		(0.007)	(0.0001)	(0.00009)
Green	-0.0003***	-		0.0006***	-
	(0.0001)			(0.0001)	
Constant	-0.25	-3.36	-4.96	-0.02	-2.84
	(0.20)	(0.26)	(0.32)	(0.26)	(0.20)
Wald Chi2	206.55***	299.97***	432.75***	311.27***	398.02***
Wald test for exogeneity	8.49***	9.78***	9.81***	12.27***	2.16***
Observations	1281	1071	1218	1113	1,218

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

5. Conclusions

We estimate CO_2 emission at the firm level using the bottom-up approach suggested by the IPCC referral approach. Further, we present the trade-off between emissions and output growth for India's manufacturing sector. This allows us to estimate the decoupling growth at the firm level for the Indian economy. The key findings are listed as follows:

1. Firms in Indian manufacturing exhibit a weak decoupling. In terms of decoupling growth, coke and allied, computer; electronics, and allied; pharmaceutical; and textiles perform best. Thus, we can say that there is a need for industrial regulation to ensure sustainable environmental outcomes.
2. Further, we investigate the relationship between technology and carbon productivity. This helps in determining the effective instruments in promoting environmental goals. We find a single threshold with a higher impact at the lower thresholds. This implies that carbon productivities are more sustainable at a lower level of R&D efficiency due to the output effect. We confirm that energy efficiency is a good proxy for policies related to emission control. Technology and the demand-side factors helped to improve carbon productivity, i.e. balancing the optimal trade-off. However, standard price mechanisms do not improve carbon productivity.
3. We also captured the inter-firm heterogeneity and estimated the club convergence. We find five convergent clubs and one divergent club and evaluate the possible factors affecting different clubs. We observe mixed findings in terms of estimating the same. More data with multi-unit assessment would help to understand the decoupling and trade-off better.
4. To explain the puzzle between decoupling and carbon productivity's contradictory results. We find consistent fluctuations in CO_2 emissions from the manufacturing sector over the last two decades. This is mainly because of endogenous production decisions, exogenous shocks, and new policy implementation. PAT cycles have been helpful in emission control in the long-run. The emission has increased because of the rebound of the R&D efficiency, mainly in the post-recession period. Factors such as energy mix and R&D intensity helped firms in emission control. These contributions are more significant post-recession. The contributions of various decomposition factors have a heterogeneous impact on different industries.

The paper simultaneously provides a solution for emission control and energy productivity improvement. The core of the contradiction occurs because factors affecting these two targets are different. R&D efficiency plays a significant role in improving CP, but policymakers should fix the threshold as the rebound threat is associated with it. Unless this is implemented, emission control will be difficult.

Our finding suggests that demand-side factors and technology help in improving carbon productivity at the aggregate level. In addition, an aggressive tax policy is not helpful. The paper also explains specific policies at a disaggregate scale. However, an improvement in carbon productivity does not ensure emission control. Efficient emission control requires an improvement of the energy mix and R&D intensity. This means cleaner production and technological advancement help in emission control. Further, a higher proportion of investment in R&D ensures a sufficiency to meet both goals. Also, the successful implementation of a cap-and-trade scheme ensures emission control and the attainment of scale efficiency.

One of the significant constraints of the analysis is the data limitation. Very few have consistently reported the data, which is even reduced since we had to adjust for the balanced panel because of the thumb rule of the threshold estimation. If more firms report their physical energy consumption data, the analysis will be more specific and robust. With sufficient data reporting, we can validate the performance of the energy schemes implemented in India that can be helpful for future research direction to address the international negotiations for climate goals.

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List of appendix

Table A-1. Correlation matrix

	lnCP	lnEE	lnEXI	lnTN	lnTP	lnETI	lnDETI	lnTFP	L.CP	lnRE
lnCP	1									
lnEE	0.94*	1								
lnEXI	0.16*	0.16*	1							
lnTN	-0.04	0.0002	0.07*	1						
lnTP	0.01	0.04	0.005	0.07*	1					
lnETI	0.02	0.04	-0.13*	-0.03	0.05*	1				
lnDETI	-0.07*	-0.05*	-0.08*	-0.01	0.07*	0.13*	1			
lnTFP	0.26*	0.14*	0.08*	-0.22*	-0.13*	-0.22*	-0.12*	1		
L.CP	0.19*	0.13*	0.11*	-0.03	-0.05*	-0.06*	0.01	0.28*	1	
lnRE	-0.04	-0.04	-0.006	-0.04	0.01	-0.04	0.07*	0.26*	0.11*	1

Note: * represents the level of significance at 5 per cent

Table A-2. Results of the unit root tests

Rho	Statistic	p-value
lnCP	0.632***	0.000
lnEE	0.634***	0.000
EXI	0.747***	0.000
lnTN	0.598***	0.000
lnTP	0.188***	0.000
lnETI	0.260***	0.000
lnDETI	0.581***	0.000
lnTFP	0.627***	0.000
L.CP	0.606***	0.000
lnRE	0.527***	0.000

Note: *** represents 1 per cent level of significance

Table A-3. Results of the cointegration test

	Statistic	p-value
Modified Dickey-Fuller t	-6.697***	0.000
Dickey-Fuller t	-7.240***	0.000
Augmented Dickey-Fuller t	-4.162***	0.000
Unadjusted modified Dickey	-14.789***	0.000
Unadjusted Dickey-Fuller t	-10.363***	0.000

Note: *** represents 1 per cent level of significance Table A-4. Multicollinearity check

Explanatory Variables	Energy Efficiency		Carbon Productivity	
	VIF	1/VIF	VIF	1/VIF
lnEXI	1.58	0.63	1.59	0.63
lnETI	1.64	0.61	1.64	0.61
lnDETI	1.14	0.88	1.14	0.87
lnTFP	5.47	0.18	5.63	0.18
lnTN	9.33	0.11	9.36	0.11
lnTP	1.04	0.96	1.04	0.96
lnETI	2.37	0.42	2.36	0.42
lnRed	7.19	0.14	7.21	0.14
lnOrange	2.20	0.45	2.20	0.45
lnGreen	1.54	0.65	1.54	0.65

Note: Estimated by the authors.

Table A-5. First-stage estimation of choice of club

Explanatory Variables	First-stage estimation				
	(10)	(11)	(12)	(13)	(14)
lnCP	0.87***	0.85***	0.86***	0.87***	0.86***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
lnEXI	0.01	0.02	0.01	0.01	0.01
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
lnTN	-0.07	-0.04	-0.08	-0.11*	-0.08
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
lnTP	0.09	0.03	0.09	0.02*	0.09
	(0.06)	(0.06)	(0.06)	(0.06)	(0.01)
lnETI	0.02	0.01	0.01	0.02	0.01
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
lnDETI	-0.02	-0.01	-0.01	-0.01	-0.01
	(0.18)	(0.02)	(0.02)	(0.02)	(0.02)
lnRE	-0.15**	-0.14**	-0.15**	-0.14**	-0.15***
	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)
lnTFP	0.07*	0.06	0.06	0.08	0.06
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
ET	-0.0001	0.002	0.0002	-	0.002
	(0.0001)	(0.0001)	(0.0001)		(0.0001)
Red	-0.0001	0.0001	0.0001	0.0001	0.0001
	(0.00009)	(0.00007)	(0.0001)	(0.0001)	(0.0001)
Orange	-0.0008	-	0.000009	0.0001	0.0009
	(0.0001)		(0.001)	(0.0001)	(0.0001)
Green	-0.0003	-	-	-0.0003	-
	(0.0001)			(0.0006)	
Constant	0.20	0.08	0.08	-0.01	0.08
	(0.31)	(0.79)	(0.26)	(0.30)	(0.31)
Adjusted R^2	0.79	0.76	0.80	0.77	0.77
F	407.73***	343.24***	407.73***	408.52***	377.02***
Observations	1281	1071	1218	1113	1,218

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1