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Will China comply with its 2020 carbon intensity commitment?

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ABSTRACT

At the Conference of the Parties held in Copenhagen in 2009 (COP15), the Chinese government announced its 2020 commitment to reduce the carbon intensity of the Chinese economy to 40–45% of its 2005 level. A number of analysts have criticised this target, indicating that these reductions can be achieved without the implementation of any active climate change policy. In this paper, we test this argument using a combined input–output based econometric projection approach and the World Input–Output Database (WIOD). Our results show that the projected carbon intensity for 2020 is likely to be 50% lower than the carbon intensity of 2005, without additional active climate change policy measures performed by the Chinese government. On top of it, our study indicates that the total volume of CO_2 emissions would be by 2020 seven times the volume of the year 2005.

1. Introduction

The latest United Nations Framework Convention on Climatic Change (UNFCCC) talks are increasingly putting more emphasis on the necessary leadership that developed nations have to take by adopting absolute emission caps, while developing countries are only encouraged to take voluntary measures. Within this context, prior to the UNFCCC meeting of November 2009 in Copenhagen (COP15), the president of China announced his country's commitment to reduce its carbon[1] intensity (CO_2 emissions per unit of GDP in current prices) by 2020 to 40–45% of its 2005 levels.[2] This commitment[3] also included an increase in the percentage use of non-fossil

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[1] Some authors refer to this objective as emissions intensity rather than carbon intensity (Stern and Jotzo, 2010; McKibbin et al., 2011; Mundaca and Cloughley, 2012).

[2] See China's "Letter including autonomous domestic mitigation actions" as an appendix in the Copenhagen Accord (People's Republic of China, 2011a). Available at: http://unfccc.int/meetings/cop_15/copenhagen_accord/items/5265.php.

[3] These decisions are not the only measures launched by China to counteract global warming. China also announced its commitment to reduce its energy intensity (aggregate use of energy per unit of GDP) by 20% between 2005 and 2010. On the other hand, there are currently five pilot projects for local markets known as "Emissions Trade Scheme" (ETS). Nevertheless, this article focuses on the first of the commitments indicated.

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fuels (essentially nuclear and renewables) up to 15% of China's total primary energy consumption during the same period (Yuan et al., 2012; Hu, 2009).

Under the Copenhagen Agreement, developed economies continued to specify their emissions reduction targets in terms of emissions levels. The Chinese commitment can be found in the Appendix II of the Copenhagen Agreement, which also includes data for other developing countries such as India, Brazil, Indonesia, Mexico and South Africa. These commitments are part of the post-Kyoto global negotiation process addressing measures to mitigate global warming.

After the COP15 meeting, the 12th Five Year Plan (12-5YP) of China approved in March 2011, reinforced its commitment to reduce the emissions intensity of output by setting a reduction target of 17% by 2015, relative to 2010. The plan also included an energy intensity target (a reduction in the ratio of energy consumption to GDP of 16% by 2015, relative to 2010), and a renewable energy target (an increase in the contribution of non-fossil fuel sources to energy consumption of 11.4% by 2015). Importantly, the plan refers to the establishment of market mechanisms to promote energy efficiency (Lu et al., 2013).

The Chinese commitments outlined above are indeed important measures that demonstrate China's awareness of its important role to reduce CO_2 emissions worldwide. However, China's commitment to emission intensity targets, in contrast to the emission level targets traditionally adopted by developed economies, raises a number of questions that complicate the debate over international emissions policy.

The Copenhagen Agreement is not a mandatory document, although the countries included in the Appendix II have announced various commitments such as objectives to reduce CO_2 emissions related with projections of the ''Business as usual'' (BaU) scenario, reductions in emissions per unit of GDP, expansion of the forest surface and investments in improving energy efficiency and bio-fuels[4] (McKibbin et al., 2011). Among all the countries that are included in the Appendix II, only China and India have taken on quantified commitments.

China is currently the largest emitter of anthropogenic carbon dioxide in the world. In 2010, China produced 24.1% of total global emissions. This level was reached within a relatively short period of time; in 1973, China had only 5.9% of the total (IEA, 2013). Yan and Yang (2010) indicate that China has been responsible for two thirds of the global increase of such emissions from 1973 to 2007.

Given the role China plays in the global governance of climate change, its commitment has awakened experts' interest and has generated the rapid development of new literature (Zhang, 2010a,b; Michinori et al., 2010; Stern and Jotzo, 2010; He et al., 2010; Steckel et al., 2011; Dai et al., 2011; Zhou et al., 2011; Yuan et al., 2012; Lu et al., 2013). On the one hand, international agreements based on carbon emissions intensity commitments, have been severely criticised as they can be used to hide the fact that a reduction in the carbon intensity could be achieved without eliminating a continuous increase of absolute carbon dioxide emissions (Stern and Jotzo, 2010). Others theoretical studies have shown that intensity targets do not necessarily perform better than level-based targets under uncertainty (Ellerman and Sue Wing, 2003; Sue Wing et al., 2006; Quirion, 2005; Marschinski and Edenhofer, 2010).

If this happens, a commitment to reduce 'carbon intensity' would be hardly more than an accounting artifice that allows the Government to do nothing to avoid global warming. The absolute levels of carbon emissions continue to increase just as they would have been done in the absence of an active carbon intensity 'commitment'.

But on the other hand, against the criticisms about how this emission intensity commitments have been established by some countries, authors such as Jotzo and Pezzey (2007) and Fischer and Springborn (2009) believe that it has positive effects on the management of economic uncertainty and helps focusing the question on technological and structural change.

Lu et al. (2013) recently suggested that the modelling framework and the underlying modelling assumptions have a notable influence on the subsequent policy conclusions. These authors arrived to this conclusion after having analysed several studies that did not provide neat general conclusions (see, e.g., Carraro and Massetti, 2011; Tavoni, 2010; Zhang, 2010b; Saveyn et al., 2012).

Either one way or another, it may happen that China can successfully achieve its carbon intensity commitments without significantly active climate change policies and at the same time, increase its absolute carbon dioxide emissions; thus leading to worse results in terms of global warming. So, in this sense, the key question to be answered in this paper is ''what is China really committed to when it comes to reducing its carbon intensity by 2020?''

We have firstly defined a reference scenario (or business as usual hypothesis, BaU) by using the latest available Input–Output (IO) Table of China (for 2009) as a basis to make a projection up to 2020. Recently, the World Input–Output Database – WIOD,[5] facilitated the access to a time series (1995–2009) of IO tables for 40 countries – including China – plus one region as ''rest of the world''. The database also includes environmental accounts for all countries with information about emission levels of the main pollutants in each of the 35 industries considered. This allows the calculation of emission coefficients for each industry, too.

Next, we will use input–output analysis provided that the so-called projected Leontief Inverse Matrix would reflect the state of the technology within the Chinese economy (Guan et al., 2008) by 2020. Likewise, an IO analysis can also facilitate the estimation of the carbon dioxide emission levels whenever there is an appropriate database to calculate the emission coefficients for any given industry (e.g., WIOD).

Generally speaking, IO analysis provides an in-depth vision of the greenhouse gas emissions by industries (Leontief, 1970; Miller and Blair, 2009); and it has become a frequently applied method as demonstrated by its rapid proliferation in the literature. Examples of national studies that specifically analyse CO_2 emissions from various IO approaches include Kondo and Moriguchi (1998) for Japan; Machado et al. (2001) for Brazil; Munksgaard and Pedersen (2001) for Denmark; Labandeira and Labeaga (2002), Roca and Serrano (2007), Sánchez

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[4] Appendix II of the Copenhagen Agreement can be found at: http://unfccc.int/meetings/cop_15/copenhagen_accord/items/5265.php.

[5] Available at www.wiod.org.

Chóliz and Duarte (2004) and Cansino et al. (2012) for Spain; Kander and Lindmark (2006) for Sweden; Mongelli et al. (2006) for Italy; Peters et al. (2006) for Norway and Tunc et al. (2007) for Turkey.

The high relevance of China as a producer of greenhouse gas emissions (GHG) also explains the increase in the number of IO analyses focused on the Chinese economy. In the current decade alone, examples of these studies can be found by Zhang (2010c), Lin and Sun (2010), Chang et al. (2010), Chen et al. (2010), Chen and Zhang (2010), Liang et al. (2010), Zhou and Imura (2011), Zhun et al. (2012) and Su and Ang (2013), among others.

However, although the literature analyzing the Chinese commitment at COP15 is emergent, there are only very few works offering estimations regarding the carbon intensity value in 2020. This paper aims to contribute to this novelty aspects in the literature.

This article is structured as follows. After this introduction, Section 2 presents the methodology and Section 3, the database. Section 4 describes the main results and discussion, while the conclusions are provided in Section 5.

2. Methodology

2.1. *Input–output analysis*

Input–output analysis revolves around the so-called input–output tables, which reflect the supply and demand of the economy in terms of products, industries and final users. By using the so-called Leontief quantity model (Rueda-Cantuche, 2011), the total output of an economy can be broken down into final and intermediate demand, as indicated in (1):

$$X = AX + Y \tag{1}$$

where X is the total industry output vector for n industries ($n \times 1$); $Z = AX$ is a matrix describing the intermediate demand of industries; A is a matrix ($n \times n$) of technical coefficients that indicates the inputs needed by each industry for its particular production; and Y is the final demand matrix ($n \times 1$) showing the final demand for all goods and services. Within this framework, we use the same number of industries and commodities (n); actually we use industry by industry IO tables provided by the WIOD database (Timmer, 2012; Dietzenbacher et al., 2013).

Reordering (1), it yields:

$$X = (I - A)^{-1}Y \tag{2}$$

where I is the identity matrix and $(I - A)^{-1}$, the so-called Leontief inverse matrix that shows the total requirements of the economy for the production of goods and services to satisfy a certain level of final demand. Moreover, with appropriate emission levels per unit of total industry outputs, C (e.g., those of 2009, as the BaU hypothesis), the Leontief model can serve to estimate the absolute levels of emissions emitted by 2020 from a certain level of total projected output requirements derived from changes in future projected final demand. That is:

$$c = \hat{C}(I - A)^{-1}Y \tag{3}$$

where ^ denotes diagonalization of the vector C of emission coefficients.

2.2. *Projecting IO tables*

The general projection problem of matrices basically consists of knowing one single base table (be they IO tables) and at least the row and column totals for the unknown table that has to be estimated. There are two different ways to approach this underdetermined problem where usually unknowns (e.g., elements of the interior tables) outnumber external constraints, in the form of row and column totals, i.e., the RAS-biproportional scaling methods; and the constrained optimisation methods (Lenzen et al., 2009).

The RAS method was first described by Stone (1961), Stone and Brown (1962) and used extensively by Bacharach (1970) to update an old given input–output table to a more current or even future period for which only the row and column totals are given. In addition, there is an extensive literature on the several improved versions of the RAS method: GRAS (Junius and Oosterhaven, 2003; Lenzen et al., 2007; Temurshoev et al., 2013); TRAS (Gilchrist and St. Louis, 1999, 2004); ERAS (Israilevich, 1986); MRAS (Paelinck and Waelbroeck, 1963); CRAS (Mínguez et al., 2009; Oosterhaven and Escobedo-Cardeñoso, 2011); and KRAS (Lenzen et al., 2009). On the other hand, constrained optimisation methods have also been used prominently in the literature with the same purposes (Stone et al., 1942; Harrigan and Buchanan, 1984; Tarancón and Del Rio, 2005, among others). However, all of these two types of methods require the row and column sums to be known but unfortunately, this is not our case for projected IO tables of China in to 2020.

The literature provides other methods that require only column sums to be known, i.e., the EUKLEMS method as described in Temurshoev et al. (2011) and the so-called SUT-RAS method proposed by Temurshoev and Timmer (2011). These authors made an empirical assessment of different projection methods showing that the SUT-RAS method seems to be superior to others.[6] Nevertheless, we argue that the empirical assessment of Temurshoev and Timmer (2011) is not fair enough with the Euro method provided that SUT-RAS uses industry output as one additional constraint while the Euro method (Beutel, 2002) does not. Hence, it is not surprising that the SUT-RAS method outperforms the Euro method, which is not restricted to any extra information on industry output. Ideally, the SUT-RAS method should have been modified so that it could have been used without such extra information on industry output in order to make a fairer comparison with the Euro method. However, this empirical assessment has not been carried out yet.

Alternatively, the industry output could have been estimated econometrically and the SUT-RAS method used instead. However, for the reasons mentioned above, we did not find sufficient evidence of the outperformance of the SUT-RAS method over the Euro method when the row and column totals are missing. As a result, we have eventually opted for the so-called Euro method (Beutel, 2002) as a way to project IO tables because it is the only method available in the literature

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[6] The methods compared were: EUKLEMS, Euro method, GRAS and five additional distance-based minimisation methods.

that can cope with the absence of information on row and column totals.

2.3. *The EURO method*

The Euro method (as conceived originally) aims at updating IO tables from one year to another and it is based on a previous version initially developed by Beutel (2002) for input–output tables and further explained by the Eurostat Manual of Supply, Use and Input–Output Tables (2008, Ch. 14).

Following Eurostat (2008), the Euro method is a robust update procedure with low cost and with limited data requirements. It exclusively uses official data and integrates all quadrants of IO tables. Row and column totals for intermediate consumption and output and the corresponding final demand structure are derived endogenously, not allowing for arbitrary changes of input–output coefficients. The method is fully consistent with supply and demand through the so-called Leontief quantity model. Therefore, it is sustained on economic grounds rather than on optimisation and/or pure mathematical techniques.

The projected IO tables are based on growth rates of macroeconomic measures of: (i) value added by industry, (ii) total final demand by use, (iii) total taxes less subsidies on products; and (iv) total imports. The method uses these official statistics as exogenous inputs, and replicates them in the derived IO tables. It represents a minimum data requirement philosophy, which fits very well with our purposes provided that it is not expected that many macroeconomic data will be available for the estimation of the Chinese IO table by 2020.

The initial IO table consists of the following components:

(a) Domestic and imported intermediate I–O matrices.
(b) Domestic and imported final demand I–O matrices.
(c) Vector of total value added of industries.
(d) Vector of total taxes less subsidies on products by industries and final use categories.

Furthermore, the following macroeconomic statistics of the projected year (e.g., 2020) are needed: the growth rates of value added per industry, final demand totals by use category, total taxes less subsidies on products and total imports. The listed data requirements mean that the vectors of value added per industry, totals of final demand categories and aggregate values of taxes less subsidies on products and imports need to be known at the projected year, too.

Differently from the standard use of the Euro method, the macroeconomic statistics will have to be projected in our paper using econometric methods instead of using available forecasts. The values for the value added of each industry were projected using autoregressive models (Gujarati, 2003). The time series considered is provided by the WIOD database (1995–2009). The values for the final demand, imports and taxes less subsidies on products have also been projected using the same econometric approach. The estimated GDP value in 2020 results in a bit more than six times the one reported by WIOD for 2009 (around three times in constant prices), though showing a similar rate to the one reported for the time period (1995–2009), ca. 5 times higher. This could be said also for constant prices. In all cases, the p-value was 0 and with the exception of one case, the R^2 value was greater than 90%.

Comparing the Chinese IOTs of 2009 and 2020, we observe that the share of value added over total output grows from 32.9% to 35.3%. In 2020, services in China would be generating a bit more than 50% of the total value added (43%, in 2009), the manufacturing activities, 40% (42%, in 2009) and agriculture, 9%, with a remarkable reduction from 2009 (15%).

From the perspective of the final demand of products, China is expected to consume more intermediates than goods and services for final uses, i.e., the share of final demand over total output would decrease from 41.3% to 39.6%. By products, final demand for services would increase from 32% to 37% in detriment of manufactured products (61% in 2020; 63% in 2009) and agricultural products (3% in 2020; 5% in 2009). Intermediate demand presents a similar performance. The demand for intermediate services would increase from 22% to 28% while the intermediate use of manufactured products and agricultural products would decrease from 66% to 63% and from 12% to 9%, respectively.

Once the macroeconomic statistics have been completed, we proceeded to run the Euro method. Hereafter, we follow the description provided by Temurshoev et al. (2011) to explain the different steps of the Euro method. Each of the iterations consists of two steps. The first step of the first iteration defines domestic and imported intermediate and final uses, the vector of value added and the vector of taxes less subsidies on products. This first estimation of the (unbalanced) IO table is basically a cell-wise arithmetic average resulting from multiplying the corresponding growth rates to the rows and columns of the initial IO table.

The total industry outputs and inputs are not equal after this first step. To make the derived IO table consistent, it is assumed that the domestic and imported input structures of industries and the totals of final uses from the first step are valid. Given this assumption, the Leontief quantity model determines consistent industry output and input levels. This second step ensures consistency of the industry outputs and inputs but however, it deviates from macroeconomic statistics, i.e., value added per industry, final uses of categories, total value added, total imports and total taxes less subsidies on products.

The growth rates initially used are then adjusted in an iterative procedure in order to make the difference between the actual and projected (in each of the iterations) growth rates minimal (less than 1%). The observed deviations are used to correct these rates in such a way that it should ensure that if the model overestimates (underestimates) the available macroeconomic statistics, the corresponding growth rates are decreased (increased). This is done through the so-called correction factors (see Eurostat, 2008 for details).

Then, the first step of the second iteration computes the projected IO table components as in the first iteration, i.e., domestic and imported intermediate and final uses, the vector of value added and the vector of taxes less subsidies on products. As was the case with the first step of the first iteration, the results do not ensure the equality of industry outputs and inputs.

The consistent industry outputs and inputs are again found using the Leontief quantity model, which is then used to derive the consistent IO table of the second iteration in exactly the same manner as defined earlier for the first iteration. However, note that now the domestic and imported input structure matrices are derived from the outcomes of the first step of the second iteration. As a result, one obtains a new deviation vector, which quantifies the difference of the projected growth rates from the macroeconomic statistics.

If the difference between the actual and projected growth rates is acceptable, the resulting IO table is the final outcome of the Euro projection. Otherwise, the steps of the second iteration are repeated until the projected variables resemble (closely or perfectly) those of the projected macroeconomic statistics. It is important to note that each such subsequent iteration begins with computing new correction factors, which are then used to correct the growth rates from the previous iteration.

The convergence in the Euro method can always be found by changing the tolerance level until convergence is reached. Further details on the Euro method can be found in Beutel (2002), Eurostat (2008) and Temurshoev et al. (2011).

Once the IO table of China for 2020 is estimated, we calculate the CO_2 emission intensity "*e*" for 2020, being defined by the ratio between China's total emissions (obtained from (3)) and total GDP for 2020, derived from the projected Chinese IO table. Following COP15 commitments (and also those of China) we assume as BaU hypothesis that emissions coefficients of 2020 remain unchanged with respect to 2009.

$$e = \frac{CO_2 \text{ emissions}}{\text{GDP}} \tag{4}$$

Finally, when the CO_2 emissions intensity figures for 2020 are compared with those for 2005, the compliance of Chinese COP15 commitment is determined.

3. Database

The data used in this paper come from the World Input–Output Database (WIOD), as described in Dietzenbacher et al. (2013). This is a free database financed by the European Union and developed with the aim to analyse the effects of globalization on trade patterns, environmental pressures and the socioeconomic development of a large group of countries. The data include world input–output tables for the 27 European Union countries and 13 other large world economies and also the corresponding national IO tables. It covers the period 1995–2009 and includes 35 industries (see Table 1) and 59 commodities.

In our research, we used the IO table (at basic prices) of China for 2009 and data on CO_2 emissions for the years 2005 and 2009. The basic structure of an IO table at basic prices can be found in Eurostat (2008).

Table 1 – Productive sectors included in WIOD.

Agriculture, hunting, forestry and fishing
Mining and quarrying
Food, beverages and tobacco
Textiles and textile products
Leather, leather and footwear
Wood and products of wood and cork
Pulp, paper, paper, printing and publishing
Coke, refined petroleum and nuclear fuel
Chemicals and chemical products
Rubber and plastics
Other non-metallic mineral
Basic metals and fabricated metal
Machinery, nec
Electrical and optical equipment
Transport equipment
Manufacturing, nec; recycling
Electricity, gas and water supply
Construction
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel
Wholesale trade and commission trade, except of motor vehicles and motorcycles
Retail trade, except of motor vehicles and motorcycles; repair of household goods
Hotels and restaurants
Inland transport
Water transport
Air transport
Other supporting and auxiliary transport activities; activities of travel agencies
Post and telecommunications
Financial intermediation
Real estate activities
Renting of M&Eq and other business activities
Public admin and defence; compulsory social security
Education
Health and social work
Other community, social and personal services
Private households with employed persons

Source: wiod.org.

4. Results

Table 2 shows, comparatively, the CO_2 emission levels by industry in 1995, 2005 and in 2020 and their overall totals. It also shows the carbon intensities by industry and for the entire economy of China for the same years.

The results included in Table 2 show that CO_2 emissions in China will likely be increased in absolute terms; up to a level that would be seven times higher than that of 2005, i.e., 33,291 Mt. This shows clearly that while carbon intensity of the economy would indeed fall, it is not expected that economic growth will decouple from the growth of total CO_2 emissions or vice versa.

Table 2 also shows that our main result is consistent with the objective expected by the Chinese government for COP15, by which it does not only achieve its most ambitious formulation (45%) but rather, according to our results, it exceeds such level with an estimated carbon intensity reduction in 2020 of 50% of its 2005 level. This trend is fully consistent with what has been happening during precedent years, i.e., 45% reduction from 1995 to 2005. Actually, we implicitly assume a slower annual average reduction rate (i.e., 4.5%) throughout the period 2005–2020 than in the earlier period (i.e., 5.8%). Graph 1 shows an overview of the paths followed by GDP and CO_2 emissions during the period 1995–2020.

Based on a more detailed analysis of industries, our results show that the objective established at COP15 can be easily achieved. In 2020, the energy industry will likely continue to be

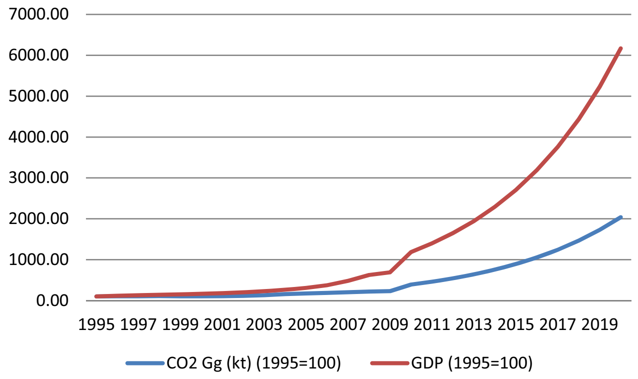
Table 2 – CO2 emission levels by industry.

	1995 Total emissions (kt)	2005 Total emissions (kt)	2020 Total emissions (kt)	1995 Emissions/ GDP (kt/1000 $)	2005 Emissions/ GDP (kt/1000 $)	2020 Emissions/ GDP (kt/1000 $)
Agriculture, hunting, forestry and fishing	104,619	134,333	454,628	142.46	58.65	13.93
Mining and quarrying	97,151	135,625	1,102,502	132.29	59.22	33.77
Food, beverages and tobacco	78,513	55,461	337,170	106.91	24.22	10.33
Textiles and textile products	57,379	44,119	222,670	78.13	19.26	6.82
Leather, leather and footwear	4261	3201	15,593	5.80	1.40	0.48
Wood and products of wood and cork	9066	9297	67,873	12.34	4.06	2.08
Pulp, paper, paper, printing and publishing	40,402	37,758	242,905	55.02	16.49	7.44
Coke, refined petroleum and nuclear fuel	49,989	81,973	527,413	68.07	35.79	16.16
Chemicals and chemical products	230,291	198,595	1,505,443	313.59	86.71	46.12
Rubber and plastics	28,255	19,661	119,809	38.48	8.58	3.67
Other non-metallic mineral	381,064	534,003	3,828,962	518.89	233.16	117.30
Basic metals and fabricated metal	305,037	507,527	4,050,088	415.37	221.60	124.07
Machinery, nec	41,955	28,307	221,166	57.13	12.36	6.78
Electrical and optical equipment	15,866	13,111	111,964	21.61	5.72	3.43
Transport equipment	17,186	18,753	146,696	23.40	8.19	4.49
Manufacturing, nec; recycling	12,269	4614	30,077	16.71	2.01	0.92
Electricity, gas and water supply	1,051,685	2,465,835	17,020,613	1432.08	1076.65	521.42
Construction	16,492	57,564	574,401	22.46	25.13	17.60
Wholesale trade and commission trade, except of motor vehicles and motorcycle	16,389	5889	59,794	22.32	2.57	1.83
Retail trade, except of motor vehicles and motorcycles; repair of household goods	5190	7252	14,846	7.07	3.17	0.45
Hotels and restaurants	7112	10,917	122,299	9.68	4.77	3.75
Inland transport	43,161	85,011	484,163	58.77	37.12	14.83
Water transport	17,268	81,746	475,190	23.51	35.69	14.56
Air transport	15,170	37,400	312,051	20.66	16.33	9.56
Other supporting and auxiliary transport activities; activities of travel agencies	3408	22,492	196,388	4.64	9.82	6.02
Post and telecommunications	1136	4710	42,395	1.55	2.06	1.30
Financial intermediation	3699	2228	35,758	5.04	0.97	1.10
Real estate activities	9193	4701	42,109	12.52	2.05	1.29
Renting of M&Eq and other business activities	8248	15,158	183,985	11.23	6.62	5.64
Public admin and defence; compulsory social security	10,542	14,754	169,926	14.35	6.44	5.21
Education	17,795	12,002	131,998	24.23	5.24	4.04
Health and social work	5445	7269	149,821	7.41	3.17	4.59
Other community, social and personal services	17,829	24,704	288,975	24.28	10.79	8.85
Total	2,723,065	4,685,970	33,289,672	3707.99	2046.03	1019.82
Variation rate					−45%	−50%
Annual average rate					−5.8%	−4.5%

the main contributor to overall CO_2 emissions, even though the carbon intensity of the Chinese energy industry would have been decreased by 50%, in line with the evolution of the rest of the economy. The same trend could be observed for the Chinese heavy industry, both in terms of total emissions and the reduction of its carbon intensity values.

Although the literature analyzing the Chinese commitment at COP15 is emergent, works offering estimations regarding the carbon intensity value in 2020 are relatively scarce and sometimes they use different methodologies and show different results.

Stern and Jotzo (2010) used a stochastic frontier model for energy intensities and analysed three different scenarios for 2020. In their first scenario (with the development of efficiency based on the BaU hypothesis), the reduction of the carbon intensity in 2020 would be 24% when compared to the 2005 values. In scenario two (based on the hypothesis that improvements in efficiency achieved between 2000 and 2007



Graph 1 – Evolution of GDP and CO_2 emissions in China (1995–2020).

would continue), the reduction would be 33%. Finally, in scenario three (based on the hypothesis that the improvements in efficiency achieved between 1971 and 2007 would continue), the reduction would be 38%.

McKibbin et al. (2011) used a general world balance model and established that the reduction of China's carbon intensity in 2020 would be 22% of the value for 2005.

Yuan et al. (2012) tested the consistency between the international and the domestic commitment of China through the projections and measures included in the 12th and 13th Five-Year-Plans (FYP). They concluded that (1) the carbon intensity targets proposed by Chinese government are consistent with the macro-level economic and social development planning; and (2) the 45% reduction target is in line with international expectations on China's responsibility of carbon stabilisation under the 450 ppm scenario.

Guan et al. (2008) used an input–output approach similar to ours. Their analysis is instead based on Ehrlich and Holdren (1971) and Hertwich (2005) and covers a longer period, spanning until 2030. To do this, they projected an IO table of the Chinese economy from 2002 up to 2030, using the RAS method (Miller and Blair, 2009). Besides, they used GDP (according to some expected growth rates,[7] i.e., 8.4% up to 2010 and 5% up to 2030) as their closing rule together with weights in the GDP for three aggregated industries; agriculture (3%), manufacturing (50%) and services (47%). The results provided by Guan et al. (2008) are based on the BaU hypothesis and showed that the carbon intensity of the Chinese economy would decrease 21% compared with its 2002 value.

Major findings of Lu et al. (2013) are that meeting China's intensity targets will require active policy intervention compared with their baseline scenario. The targets could be met without substantial growth effects.

In sum, these five articles concluded that China must promote ambitious policies aimed at reducing its CO_2 emissions. In particular, Stern and Jotzo (2010) and McKibbin et al. (2011) concluded that these policies are necessary if China wants to reach the objective accepted at COP15. In other words, they singled out that this objective would be unachievable using the BaU hypothesis. Lu et al. (2013) used an intertemporal, computable general equilibrium model of the world economy with 12 sectors (instead of 35, as in this paper). The simulation policy of Lu et al. (2013) takes the form of a carbon tax, whose tax revenues were delivered back as a lump sum transfer to the household sector. Their conclusions are in line with McKibbin et al. (2011).

However, our analysis confirms instead the results of Mundaca and Cloughley (2012), who offered a different view of the question analysed herein. Their research is, nonetheless, retrospective as it analyzes the 1990–2007 period for the economies of Sweden, Great Britain and China. Although their research does not include all CO_2 emissions, it focuses only on emissions coming from the combustion of fossil fuels. These authors found that the ratio between CO_2 emissions and GDP decreased by 50% at the end of that period; this result is only due to China's economic growth and not to the de-carbonization of the primary energy mix. Their results coincide almost exactly with our findings, although the CO_2 intensity is the endogenous variable in this study while it is an explanatory variable in theirs.

A study by the United States Energy Information Agency (EIA-IEO, 2009) coincides in some aspects with Mundaca and Cloughley (2012). The EIA-IEO report develops a decomposition analysis of CO_2 emissions from the Kaya equation and includes a historical analysis of carbon intensity behaviour for a number of areas and nations of the world. It also included a projection up to 2030. The changes of CO_2 emissions are decomposed into energy intensity, carbon dioxide intensity, income per capita and population factors, which are the most frequent used factors from the Kaya equation. In the case of China, the energy and carbon dioxide intensities drive the emissions downwards while the growth of the other two (i.e., income per capita and population) has the opposite effect. So, the carbon intensity would fall from 1 Tm CO_2 for each $1000 of GDP in 2006 to 0.56 Tm CO_2 in 2020; this 44.2% decrease must also take into consideration the fact that it was measured in dollars consistent with 2005. The conclusions reached by Carraro and Tavoni (2010) are similar as they used data from the International Energy Agency, too. Other modelling studies that also suggest that China's emissions intensity targets are not binding are International Energy Agency (2011) and Saveyn et al. (2012).

Table 3 – CO_2 intensities for some major economies.

	1995	2005	2020	Rate var % (1995–2020)
Brazil	100	118.18	65.22	−34.78
China	100	55	33	−67
Germany	100	86.02	64.29	−35.71
India	100	67.95	58.6	−41.4
Japan	100	119.89	100	0
UK	100	52.4	47.53	−52.47
US	100	63.25	50	−50

Source: Own elaboration from WIOD.

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[7] Annual growth rates widely vary among studies. Lu et al. (2013) considered that the average annual growth rates of real GDP and emissions in the baseline for China over the period 2010–2035 will be 4.7% and 4.0%, respectively. Yuan et al. (2012) considered an annual GDP growth rate of 7% during the 12th Five-Year-Plan (FYP) period and 6% during the 13th FYP period.

As a complement to the previous literature review, Table 3 depicts CO_2 intensities for some major economies. China clearly performs the deepest decrease during the period 1995–2020.

5. Conclusions

China's commitment at COP15 has generated an increasing number of reports in the literature, justified by the crucial role that the Chinese economy plays in the global emissions of GHG. There are a variety of methodological approaches that can be used to check the extent to which the commitments of China under the COP15 agreements are ambitious or merely non-restrictive measures that will be fulfilled even without active national climate change policies. Following Guan et al. (2008), we have used input–output analysis but with three significant improved features that enhance the quality of our results. These are:

(a) We have used the World Input–Output Database, which accounts for 35 industries instead of three aggregated sectors; being fully consistent with the Chinese National Accounts.
(b) We have used time series analysis to make projections of the main macroeconomic magnitudes, relevant to the projection of the Chinese IO table for 2020 instead of assuming constant growth rates of GDP in two different subperiods.
(c) We have used the EURO method instead of the RAS method. This method is particularly useful whenever the row and column totals are not known and whenever negative values appear in the interior of the IO tables (changes in inventories. . .).

Within this improved methodological context and similar to other studies mentioned above, our main result indicates that China's economy could reach the most ambitious formulation of the objective to reduce its carbon intensity, as established in 2009 at COP15, without forcing the country to implement more active policy measures to fight against climate change. In other words, keeping the current trend of the carbon intensity reduction over the period 1995–2005 is sufficient for the Chinese authorities to achieve its own target for 2020, even with a bit slower average annual reduction rate of its carbon intensity.

Achieving the objective established at COP15 would not achieve a reduction in the total CO_2 emission values, which would be instead seven times greater than that registered in 2005. Therefore, the Chinese economy would fail to achieve a decoupling of economic growth from growth in the total volume of CO_2 emissions. From the perspective of the effectiveness of policies to mitigate CO_2 emissions, setting targets in terms of carbon intensity might not be a good decision. Moreover, in any case, these values should be referenced to a specific base year or in terms of purchasing power parity to avoid price distortion effects.

This paper indicates that Chinese 'promises' of COP15 will likely require no significant new policies against climate change; thus, some observers could see them as misleading. As a matter of fact, if China takes on the role of global leadership in climate change policies, they clearly need to do more than what they committed themselves to do under COP15.

As two illustrative examples, the high relevance of the power and the heavy manufacturing industries in terms of CO_2 emissions can serve to guide the Chinese government towards the identification of various industry related policy measures to be implemented progressively until 2020 to fight against climate change. In the first case, the Chinese primary energy mix that would continue to be dominated in the BaU scenario by the use of coal to produce electricity (IEA, 2013) shows an area where major reductions can be achieved by intervention. Recently, this is also supported by Arto et al. (2013) using the WIOD database. In the second case, improvements in the energy efficiency of the heavy manufacturing industry would allow significant improvements towards decoupling economic growth and CO_2 emissions growth in China.

Our findings do not imply that Chinese Authorities are not concerned about the need to improve active policy measures against Climate Change. The Chinese government has formulated and implemented extensive energy and climate policies. In China's 12th Five Year Plan (12-5YP) approved in March 2011, China also included an energy intensity target (a reduction in the ratio of energy consumption to GDP of 16% by 2015, relative to 2010), and a renewable energy target (an increase in the contribution of non-fossil fuel sources to energy consumption of 11.4% by 2015). In fact an increase of the share of non-fossil energy in primary energy to 15% by 2020 was also announced at the same time that the CO_2 intensity commitment. China has to reduce its dependence on fossil fuels to the domestic economic growth, in accordance with China's domestic agenda to pursue economic growth and energy security.

To meet these targets, the 11th and 12th-5YP include important political measures. In general, these policies address the energy and climate challenges that China faces: developing renewable energy and improving energy efficiency. A comprehensive list of measures is available at Yuan et al. (2012). We add the five pilot projects of Emissions Trade Schemes (Lo, 2013) to this list. They show that market mechanisms are becoming more and more dominant in the Chinese economy, thus being the effectiveness of command-and-control policies progressively less strong.

In sum, our findings suggest that the announcement made by the Chinese government in 2011 was somewhat conservative because it was relatively easy to meet and, on the other hand, that commitments fixed in terms of CO_2 intensities are not an effective way to implement effective agreements within the current post-Kyoto context. Indicators showing carbon intensities per unit of energy consumption and energy consumption per GDP could be better options.

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