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Discussion Paper

Understanding the Role of Renewable Energy in Import Demand for Petrochemicals

Is the Prevailing Perception More Imagined Than Real?

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October 2024 | Doi: 10.30573/KS--2024-DP40

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Abstract

The prevailing perception is that the transition to renewable energy will lead to a decrease in demand for hydrocarbons and petrochemicals. The present work empirically demonstrates that this common sense may be more imaginary than real: it finds evidence that the renewable energy development may have a positive impact on hydrocarbons through its growing demand for petrochemicals.

To get rigorous results, we employ the state-of-the-art panel time series methods that are capable of accounting for main issues of panel data (e.g., cross-sectional dependence, non-stationarity, and heterogeneity) and providing insights for individual countries. The methods are applied to data spanning from 1996 to 2022 for seven countries, all of which are among the top developing nations in terms of their installed renewable capacity. Our key finding that renewables have a positive impact on the demand for petrochemicals import is robust to various model specifications that we considered in the empirical analysis. Using the polymer intensities of the renewable energy systems and the estimated elasticities of demand for petrochemicals import, the global petrochemical polymer demand to meet projected renewable energy system penetration in a net-zero emissions scenario by 2050 was quantified to be in the range of 155 to 223 million metric tons (which translates to a growth in equivalent crude oil demand of 0.80 to 1.13 million barrels per day between 2025 and 2050), depending on the energy system design preferences. Import demand, which creates an opportunity for petrochemical exporters and arises mainly from growth in the economies of India and China, accounts for between 67 and 96 million metric tons of the polymer materials.

The insights for the policymaking in the petrochemical-importing economies are that their renewable transition will necessitate an increase in petrochemical imports. Developments in manufacturing of renewable energy technologies and higher domestic prices of petrochemicals relative to international prices would further boost these imports. Policymaking in the petrochemicals-exporting economies should consider that the findings may suggest opportunities for the expansion of petrochemicals and related sectors, such as hydrocarbons.

Key words: Renewables, petrochemicals, hydrocarbons, imports, developing economies, panel time series analysis.

1. Introduction

In 2015, all the United Nation (UN) member countries adopted 17 Sustainable Development Goals (SDGs) with 169 targets to be achieved by 2030 (https://sdgs.un.org/goals). Two of these goals constitute supportive steps towards implementing the Paris Agreement in practice. Energy transition from hydrocarbon to renewables sources is considered essential for achieving goal 7 – Affordable and Clean Energy, and goal 13 – Climate Action. Therefore, many studies have investigated various aspects of the renewable energy transition ranging from its economic growth effects to carbon emission features (e.g., see Elshurafa, Hasanov, and Hunt 2024 and references therein).

Renewables as sources of energy are alternatives to fossil fuel sources, including hydrocarbons. Consequently, the renewable energy transition may negatively affect the hydrocarbon sector through two main channels. First, through its effect on the heating and cooling (representing about half of the global final energy consumption) demand for fossil fuels.[1] Second, the energy transition may reduce the transport sector's demand for hydrocarbons. This sector is considered the main source of demand for crude oil, representing around 60% of the global consumption of crude oil (IEA 2021a). Nevertheless, some forecasts indicate that this demand may decline by 40%, driven by an anticipated boom in electric vehicle adoption (IEA, 2022). To this end, the prevailing view in the literature is that expansion in renewables would diminish the hydrocarbon industry (Genc & Kosempel 2023; OIES 2021). Such a view has formed (or largely contributed to) the prevailing common sense in the research community and policymaking that the development of the renewable energy sector is crowds out the hydrocarbon sector (Puyo et al. 2024; IPCC 2022; Giannikopoulos et al. 2022; Welsby et al. 2021; IEA 2021b).[2]

The adverse effect of renewables on hydrocarbon described above is intuitive from the energy demand standpoint. From the non-energy use (e.g., non-combustion or feedstock) demand standpoint, however, it can be thought that the growing renewables may introduce opportunities for the hydrocarbon sector. Such opportunities have mostly materialized through the expected growth in petrochemicals, such as plastic and rubber, driven by the planned increase in the demand and production of renewable energy equipment, such as solar panels and wind turbines, as projected by the World Energy Outlook (WEO 2022), among others.[3] The renewable energy industry relies heavily on petrochemical products (USGS 2018; Rosenbloom 2024). Essential polymers, like ethylene and polyurethane, from petrochemicals, are crucial for manufacturing solar panels, which convert sunlight into energy. Similarly, the production of wind turbines necessitates materials such as steel, which is manufactured using powdered coal and natural gas. Additionally, various parts of the turbines, including engine houses, airfoils, and rotor blades, are crafted using resins sourced from petrochemical-based products, while oil-based lubricants are essential for the

gearbox (e.g., see Rosenbloom 2024; Fourteau 2022; IEA 2018; USGS 2018). As IEA (2018) and Bennett and Page (2015) discuss, petrochemicals are rapidly becoming the largest driver of global oil demand for feedstock. Obviously, an expansion in the petrochemical sector will require more feedstock to be consumed, which is predominantly coming from the hydrocarbon sector, such as ethane, methane, naphtha, and liquefied petroleum gases (see projections in IEA 2018; WEO 2023, 2019).[4] Thus, the emphasis of international energy agencies such as IEA and IRENA, through their future energy outlooks also suggest opportunities for substantial growth in the demand for petrochemical products.

To summarize the discussions above, on the one hand, many studies considered hydrocarbons and renewables as alternative sources to meet energy demand and concluded an inverse relationship between the two. On the other hand, to date there is no dedicated applied research study estimating the impact of the renewables industry, particularly solar and wind, on hydrocarbons particularly via demand for petrochemicals such as plastics and rubbers using realized/actual data, to the best of our knowledge.[5] To this imbalanced end, the prevailing view in the research literature and (to some extent) in the policymaking is that expansions in renewables crowds out hydrocarbons, which should translate to a similar adverse effect on petrochemicals derived from hydrocarbons.

This present work empirically demonstrates that the above-mentioned prevailing perception may be more imaginary than real by conducting a decent econometric analysis. This is the primary contribution of this study.

Dictated by the data availability, we consider the top seven developing economies in terms of renewable energy scale and investigate their petrochemicals imports.[6] We consider petrochemicals because the renewables industry creates demand for petrochemicals, such as plastics and rubber, but not directly for hydrocarbons as discussed above. The advantage of considering petrochemicals' import demand not aggregate demand is that derived policy insights could be useful for not only importing countries but also exporting ones.

In addition to its primary contribution above, this work possesses a few other merits. First, to the best of our knowledge, this is the first study to numerically assess the impact of renewable industry on petrochemical imports. The renewable energy transition is a phenomenon that every industry including petrochemicals and hydrocarbons, should assess for its potential effects. Second, we base our analysis on the theory of import demand and expand upon it by incorporating renewable installed capacity. Such an extension aligns with previous studies on import demand (e.g., Adam, Katsimi, and Moutos 2012; Konstantakopoulou 2020; Doroodian 1987; Hosen 2023; Chani, Pervaiz, and Chaudhary 2011). Furthermore, it can be characterized as a combination of theory-driven and data-driven approaches – a practice widely employed and endorsed for applied research by leading scholars (see, for example, Hendry 2018; Castle and Hendry 2017, 2019; Hendry and Johansen 2015; Juselius 2021, 2010; Campos et al. 2005). Third, to obtain sound results and suggest grounded policy insights, we address the main issues of the panel data, namely cross-sectional dependency, non-stationarity, and heterogeneity using the state-of-the-art panel time-series methods. Fourth, many panel studies conducted pooled analysis and ended up suggesting the same policy recommendations for all countries in the panel. Such one-size-fits-all type recommendations ignore country specificities and, hence, would not be as useful for individual countries' policymaking. To avoid this and be able to suggest country-specific policy recommendations, we estimate petrochemicals import demand function for each individual country separately.

This study is organized as follows. Section 2 presents the theoretical framework and empirical model of the study. Data is discussed in Section 3. Section 4 describes the empirical analysis strategy and econometric methodology. The results of the empirical analysis are documented in Section 5 and their discussion is given in Section 6. Section 7 concludes the study with some policy insights.

2. Theoretical Framework and Empirical Model

The theoretical underpinning of our study is the international trade theories developed in Leamer and Stern (1970), Goldstein and Khan (1985), Rose and Yellen (1989), and Rose (1990). According to these theories, in the framework of the imperfect substitutes model of a Marshallian demand, total quantity of imports demanded by a country is related to its real income (or real expenditure or any other scale variable that captures domestic demand conditions) and relative prices. This is the standard form of the import demand function and widely used in empirical studies (e.g., see Carone 1996; Adam, Katsimi, and Moutos 2012). It can be expressed with the following un-specified function as:

$$M = f(Y, PR) \tag{2.1}$$

where M and Y are demand for goods to be imported and income of the importing country, respectively. PR is the relative prices. It can be defined as $PR = \frac{P^F}{P^D}$. That is, the ratio of the prices of imported goods in the international markets (P^F) to the prices of imported goods in domestic markets (P^D), both expressed in the same currency, for example in US$, respectively. Usually, P^D is in local currency multiplied by the exchange rate of say US$ against the local currency. This is to express the domestic price in US$, so both prices will be in the same currency, i.e., US$.

As discussed above, this research is interested in exploring the role of renewable energy in the import demand for petrochemicals, to come up with policy insights that are useful for both importers and exporters of petrochemicals. Therefore, we include our variable of interest, that is, renewable energy (*REIC*) in the equation of petrochemicals import demand (*MP*). Note that extending a standard import function with a variable of interest is widely considered in literature. For example, the standard import demand specification is extended by income inequality in Adam, Katsimi, and Moutos (2012) and Konstantakopoulou (2020), by transitory income in Doroodian (1987), by foreign exchange reserves in Hosen (2023) and by expenditure components in Chani, Pervaiz, and Chaudhary (2011). Moreover, extending theoretical framework (e.g., equation (2.1)) with the variable of interest, that is, *RE* can be considered as the combination of theory-driven approach with data-driven approach, which is widely used and also recommended for empirical studies by seminal scholars (see e.g., Hendry 2018; Castle and Hendry 2017, 2019; Hendry and Johansen 2015; Juselius 2021, 2010; Campos et al. 2005). Such an extended equation in the case of the panel data and econometrically estimable form can be expressed as follows:

$$\begin{aligned} ln(MP_{it}) = \alpha_0 + \alpha_1 ln(Y_{it}) + \alpha_2 ln(PR_{it}) \\ + \alpha_3 ln(REIC_{it}) + \varepsilon_{it} \end{aligned} \tag{2.2}$$

where, *ln* denotes the natural logarithm, ε_{it} denotes the error term. α_0 is the constant term, while $\alpha_1 - \alpha_3$ are the

elasticities of petrochemical imports with respect to income, relative prices, and renewable energy, respectively. $\alpha_0 - \alpha_3$ coefficients are to be estimated econometrically. *i* and *t* indicate sections/panel members and time, respectively. $i = 1, 2, \ldots N$ and $t = 1, 2, \ldots T$. *N* and *T* are the number of panel members and time series observations, respectively.

Theoretically, one would expect $\alpha_1 > 0$, meaning that demand for import increases when the income of the importing country rises. Conversely, $\alpha_2 < 0$, suggests that a country's demand for imports should decrease if the international market prices of petrochemicals are higher than the domestic prices, both expressed in the same currency (e.g., US$). Conceptually, we expect $\alpha_3 > 0$ based on our discussion above.

The coefficients in equation (2.2) are the pooled coefficients. In other words, they are the same for each member/section of the panel. This is the traditional panel methodology. However, one of the merits of our study, as we discussed above, is that we will use modern panel methodology, which allows us to estimate the coefficients of a given relationship for each panel member/section. This is extremely important as it enables us to provide section-/member-specific policy recommendations, which cannot be derived from the application of the traditional panel methodology. Thus, our empirical model of the petrochemical imports in the case of section/member-specific coefficients can be expressed as:

$$ln(MP_{it}) = \alpha_{0_i} + \alpha_{1_i} ln(Y_{it}) + \alpha_{2_i} ln(PR_{it}) + \alpha_{3_i} ln(REIC_{it}) + v_{it} \quad (2.3)$$

3. Data

In the ideal case, we should consider renewable manufacturing, mainly solar panels and wind turbines, in the analysis. The available data show that the top countries of solar panel manufacturing in 2021 are China, Vietnam, Malaysia, South Korea, United States, India, Thailand, Taiwan, Europe, Japan, Singapore, and Canada; with China having the share of 75% out of 100%.[7] Regarding wind turbines, nine out of the top 15 manufacturers in 2022 are located in China while the remaining six are in Germany, Denmark, Spain, and France.[8] The above are the only data available on manufacturing of solar panels and wind turbines. Obviously, they are not sufficient for our econometric analysis because we need data by country and year, and that is not available. Therefore, we adopt data on the installed capacity of solar and wind power systems, which are the closest to the representation of the solar panels and wind turbines manufacturing. We take this position because one can reasonably think that manufacturers of these renewable energy systems are more likely to consider the domestic market first before exploring export opportunities to other countries, considering the pressing climate change related local and international commitments, policies, agreements, and measures, in addition to domestic energy security and sustainability.

To this end, we considered the top seven developing countries in terms of the share of installed solar and wind power generation capacities over the last 10 years, using data from the Statistical Review of World Energy database 2023 release. They are ranked as China, India, Brazil, Turkey, Mexico, Chile, and Thailand.[9]

The time dimension of our sample covers 1996-2022. The starting year of the sample is dictated by the availability of the data on renewable installed capacity for solar and wind energy systems. Table 1 documents the variables through their definition, measurement, and source.

Table 2 presents essential descriptive statistics for the variables of petrochemicals import and the installed capacity of solar and wind power systems in the countries under consideration.

Figure 1 illustrates the same variables for each country over the time sample of 1996-2022.

Table 1. Variables used in the study.

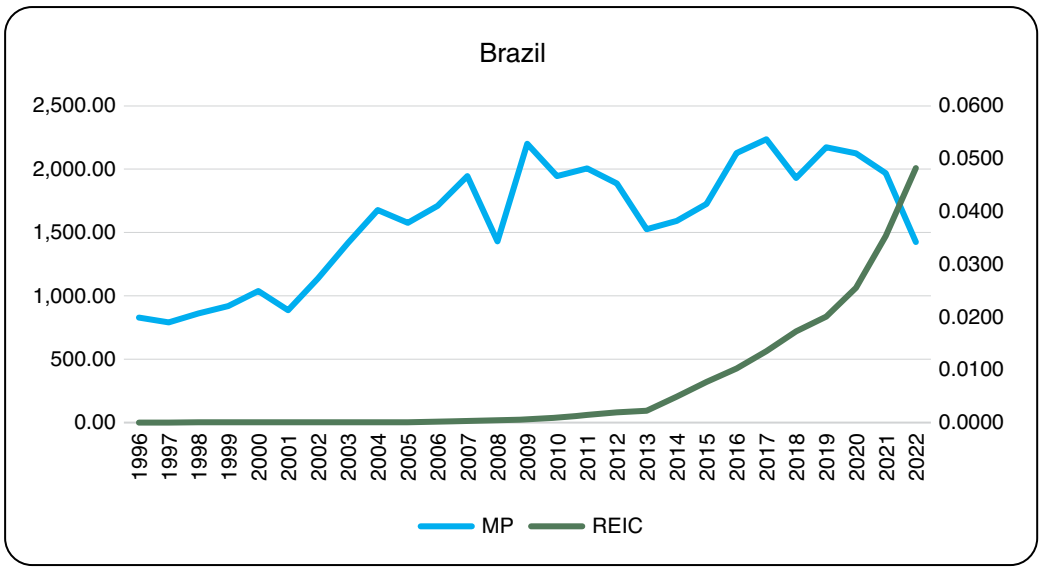
Variable	Definition	Measurement	Source
Imports of Petrochemicals (*MP*)	The import volumes of the petrochemical products of rubber and plastic.	Thousand tons	United Nation Commodity Trade database (UNCOMTRADE).
Renewable Energy Installed Capacity (*REIC*)	The installed capacity of solar and wind power systems.	Megawatts	Statistical Review of World Energy, 2023 release.
Income (*Y*)	Manufacturing value added.	Million US$ at 2015 constant prices	WDI database, 2023 release.
Relative Prices (*PR*)	The ratio of the international prices of rubber and plastic to domestic prices. The international price of rubber and plastic is calculated as the ratio of value of these products in thousand US$ to their volume in thousand tons. The resulting series is divided by the figure in 2015 to get index as 2015=100. The domestic price is represented by the GDP deflator, 2015=100. This is dictated by the data availability, as we could not find either domestic petrochemical prices or manufacturing/ industry prices for all countries and sample span under consideration.	Index, 2015=100	The value and volume of rubber and plastic are from UNCOMTRADE. GDP deflator data are from WDI database, 2023 release.

Table 2. Descriptive statistics of the variables.

	MP, in thousand tons			*REIC, in Megawatts*		
Country	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**
Brazil	1,595.20	2,236.89	790.77	7,072.24	48,241.99	0.00
Chile	140.22	197.87	44.70	1,473.25	10,080.12	0.00
China	18,009.07	36,100.30	2,945.83	141,037.83	759,092.13	1.00
India	2,377.18	4,635.83	550.62	25,058.14	105,075.86	0.00
Mexico	2,340.98	5,306.39	949.67	3215.56	16,338.55	10.00
Thailand	9,157.34	14,264.14	4,717.03	1,243.68	4,610.60	0.00
Turkey	1,510.27	3,565.57	223.93	4,258.76	20,822.62	0.00
Panel	5,018.61	36,100.30	44.70	26,194.21	759,092.130	0.00

Notes: *Max and Min denote maximum and minimum values; there are 27 annual times series observations from 1996 to 2022 for each variable in each country.*

Figure 1. Petrochemical imports (left axis, blue line) and renewable energy installed capacity (right axis, green line).



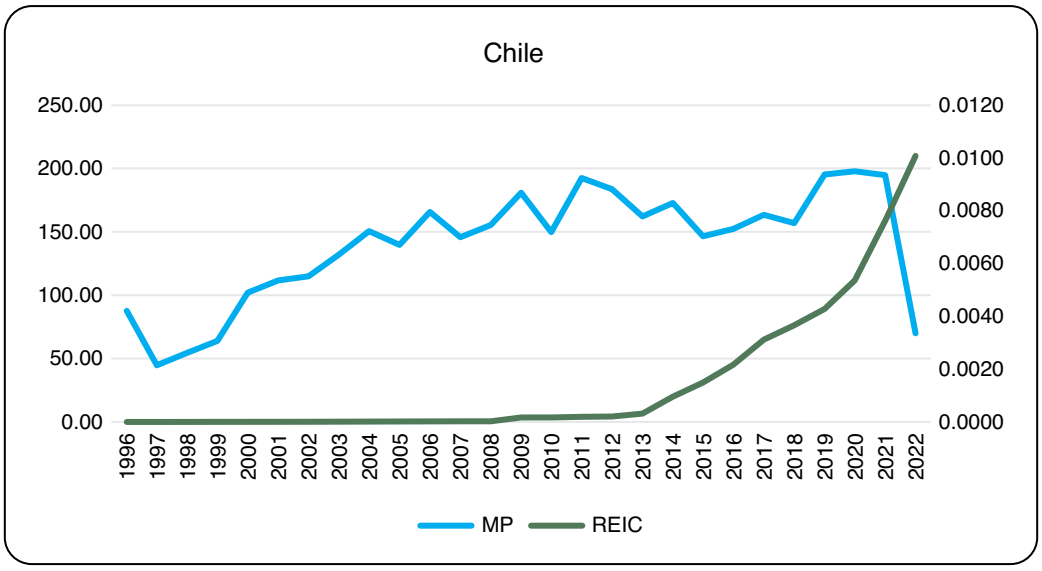
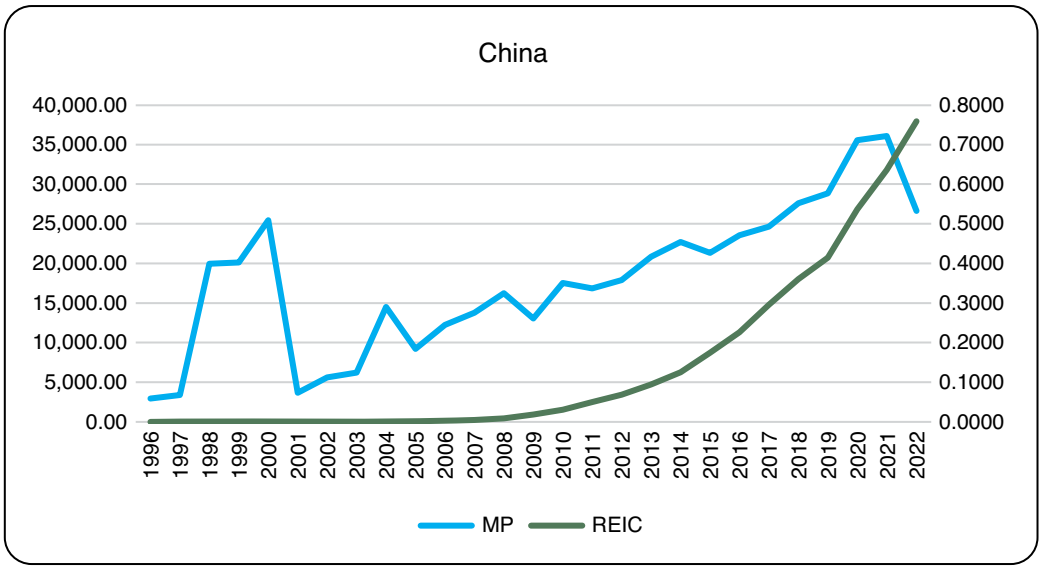


Figure 1. (*continued*)



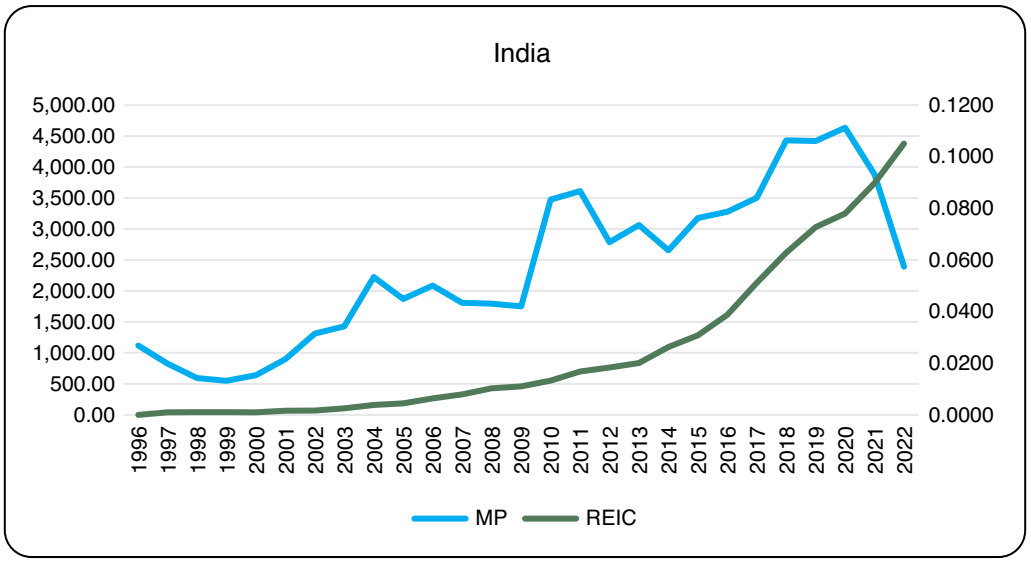
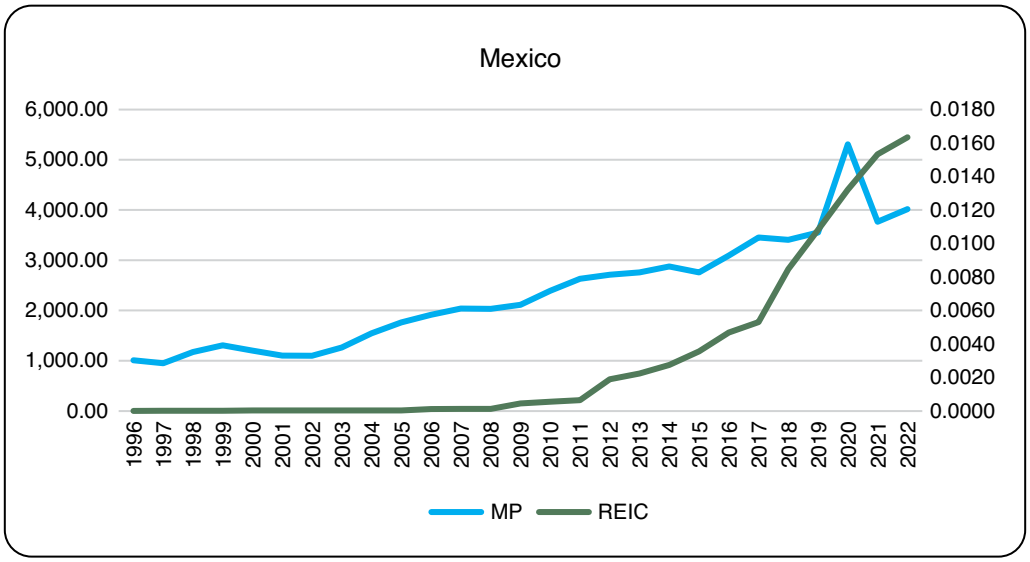
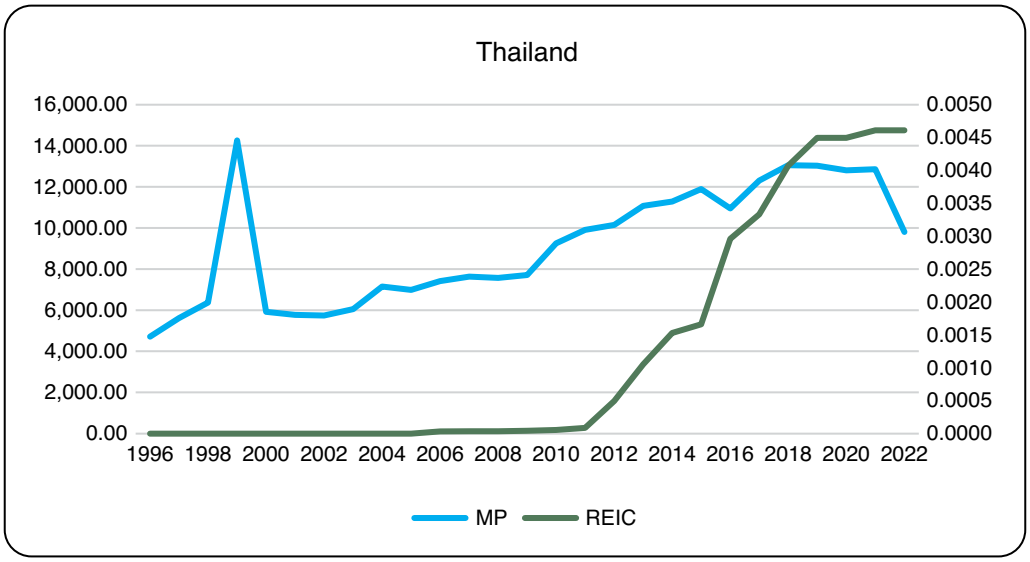
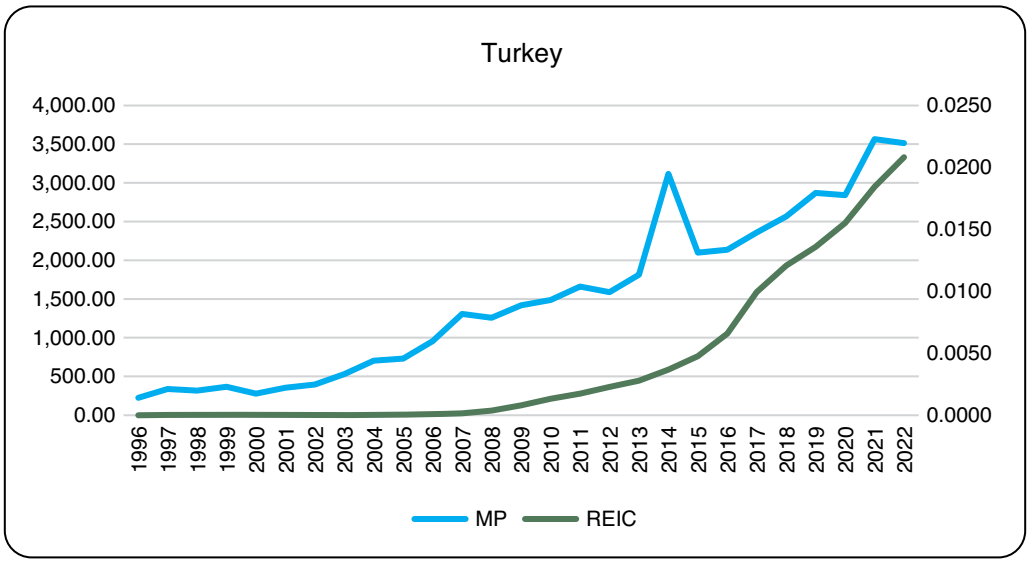


Figure 1. (*continued*)







One of the noteworthy observations from the figure is that installed renewable capacity increased significantly since 2012 or so in each country. Another observation is that petrochemical imports have been increasing over time, although they declined in 2022 in almost every country. This decline was mainly due to low growth in the selected economies and the Russia-Ukraine conflict (McKinsey & Company 2022; S&P Global 2022). Lastly, installed renewable capacities are smooth over time with less variation, whereas petrochemical imports demonstrate more variation in the countries under consideration. Even the latter variable has spikes in some countries, such as China, Mexico, Thailand, and Turkey.

4. Empirical Analysis Strategy and Methodology

Figure 2 illustrates our strategy for the empirical analysis while Table 3 presents panel methods that can be potentially considered, depending upon the conclusion of the strategy.

A takeaway from Figure 2 is that one should use second-generation panel methods to test for unit root, cointegration and to estimate the long-run relationship between petrochemical imports and explanatory variables if the data demonstrate cross-sectional dependency (CD), which will be decided based on the CD test results.

In the case of two explanatory variables (regressors), the panel version of the Autoregressive Distributed Lags (ARDL) model – assuming heterogeneity of all coefficients, i.e., the Mean Group (MG) method due to Pesaran and Smith (1995) – in the level form of the variables, can be written as follows:

$$Y_{it} = b_{0i} + \sum_{k=1}^{p} b_{1ik} Y_{i,t-k} + \sum_{k=0}^{q} b_{2ik} X_{i,t-k} + \sum_{k=0}^{q} b_{3ik} Z_{i,t-k} + e_{it} \quad (4.1)$$

where Y is the dependent variable; X and Z are the regressors; $i = 1,2,\ldots,N$ and $t = 1,2,\ldots,T$ denote panel member and time, respectively; k changes from unity to p for the dependent variable and from zero to p for explanatory variables; p and q are the maximum numbers of lags for the dependent and explanatory variables, respectively.

$$e_{it} = \Gamma_i f_t + \varepsilon_{it}$$

where f_t is an $m \times 1$ vector of unobserved common factors, Γ_i is an $m \times k$ vector of factor loadings and ε_{it} is the idiosyncratic error. It represents the part of the error that is unique to each panel member and time period, after accounting for the common factors. It captures purely random shocks that are unrelated to the unobserved common factors.

To approximate unobserved common factors, f_t', the MG in equation (4.1) can be augmented by cross-sectional averages (CSAs) of the variables, $\bar{Y}_t$, $\bar{X}_t$, and $\bar{Z}_t$ as discussed in Pesaran (2006), Chudik and Pesaran (2015) among others.

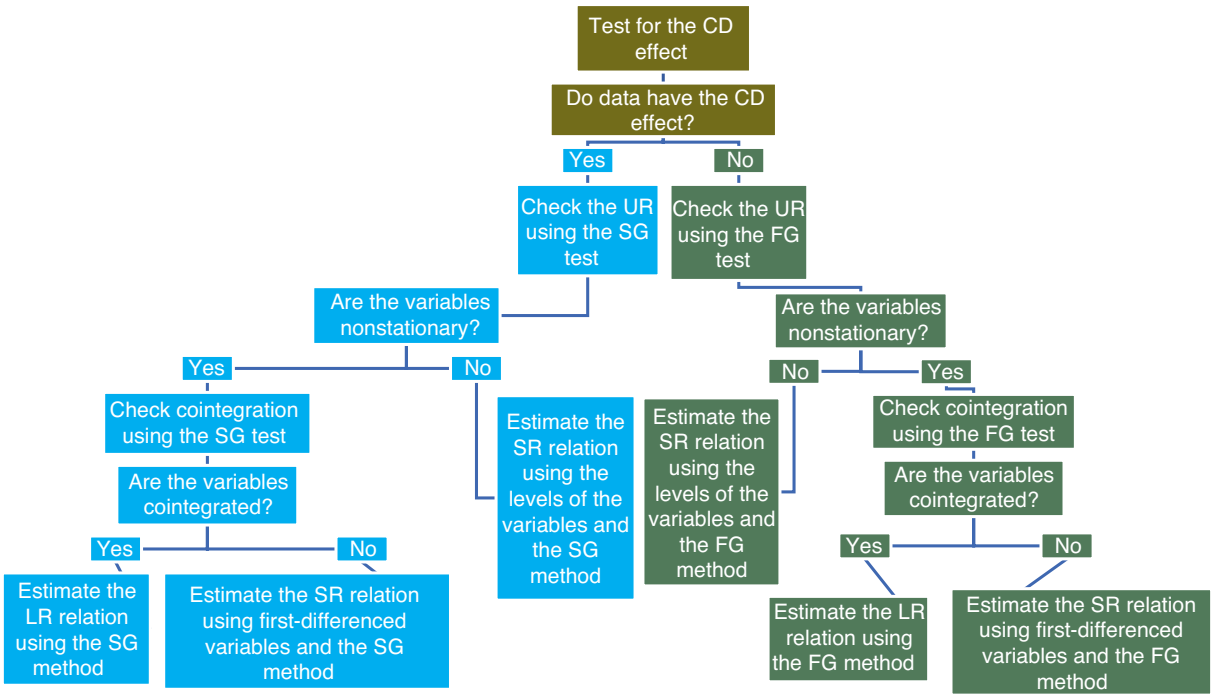
Where $\bar{Y}_t = N^{-1}\sum_{i=1}^{N} Y_{jt}$; $\bar{X}_t = N^{-1}\sum_{i=1}^{N} X_{jt}$; $\bar{Z}_t = N^{-1}\sum_{i=1}^{N} Z_{jt}$.

Note that contemporaneous and lagged values of CSAs of the variables can be used for this purpose. Pesaran (2007) discusses that usually one lag of the level and contemporaneous value of the first difference of CSAs are sufficient to filter out the effects of the unobserved common factors, f_t'. It further notes that the lag orders can be high if N, i.e., number of cross-sections is large. Thus, the MG with CSAs of the variables can be expressed in the following equation:

$$\begin{aligned} Y_{it} = {} & b_{0i} + \sum_{k=1}^{p} b_{1ik} Y_{i,t-k} + \sum_{k=0}^{q} b_{2ik} X_{i,t-k} \\ & + \sum_{k=0}^{q} b_{3ik} Z_{i,t-k} + \sum_{k=1}^{p1} \alpha 1_k \bar{Y}_{t-k} \\ & + \sum_{k=0}^{p2} \alpha 2_k \bar{X}_{t-k} + \sum_{k=0}^{p3} \alpha 3_k \bar{Z}_{t-k} \\ & + \sum_{k=1}^{p4} \alpha 4_k \Delta \bar{Y}_{t-k} + \sum_{k=0}^{p5} \alpha 5_k \Delta \bar{X}_{t-k} \\ & + \sum_{k=0}^{p6} \alpha 6_k \Delta \bar{Z}_{t-k} + \varepsilon_{it} \end{aligned} \quad (4.2)$$

where $\alpha 1_k$ to $\alpha 6_k$ are the coefficients to be estimated econometrically. ε_{it} is the idiosyncratic error as defined above. $p1 - p6$ are the lag orders and not necessarily equal to each other.

Figure 2. Empirical analysis strategy.



Source: *Re-produced from Hasanov et al. (2024).*

Note. *CD = Cross-sectional dependence; UR = Unit Root; FG = First Generation; SG = Second Generation; LR = Long-run; SR = Short-run.*

Table 3. Methods to be considered.

Method	PURT	PCT	Long-run Estimation	Short-run Estimation
First Generation	Maddala and Wu (1999) Hadri (2000)	Pedroni (1999, 2004), Kao (1999)	PDOLS, PFMOLS, MG or PMG	PECM or PDR with GTSMS
Second Generation	Pesaran (2007)	Westerlund (2007)	CCEMG or CCEP AMG	

Note. *PURT = Panel Unit Root Test; PCT = Panel Cointegration Test; PDOLS = Panel Dynamic Ordinary Least Squares, PFMOLS = Panel Fully Modified Ordinary Least Squares, MG = Mean Group; PMG = Polled Mean Group, CCEMG = Common Correlation Effect Mean Group; CCEP = Common Correlation Effect Pooled; PECM = Panel Error Correction Model; PDR = Panel Dynamic Regression; GTSMS = General to Specific Modeling Strategy.*

Source: *Re-produced from Hasanov, Liddle, and Mikayilov (2018).*

The long-run coefficients for X and Z can be calculated from (4.2) using the formulas below:

$$\varphi_{Xi} = \frac{\sum_{k=0}^{q} b_{2ik}}{1-\sum_{k=1}^{p} b_{1ik}}; \varphi_{Zi} = \frac{\sum_{k=0}^{q} b_{3ik}}{1-\sum_{k=1}^{p} b_{1ik}} \quad (4.3)$$

Thus, the long-run equation of Y can be expressed as follows:

$$Y_{it} = \varphi_i + \varphi_{xi} X_{i,t} + \varphi_{zi} Z_{i,t} + \varepsilon_{it} \quad (4.4)$$

5. Results of the Empirical Analysis

This section provides the results of the econometric estimations and testing. The first part of the section presents the results of cross-sectional dependence, unit root, and cointegration tests, while the long-run estimations results are given in the second part.

We used recently developed tests of Pesaran (2015), Fan, Liao, and Yao (2015), and Pesaran and Xie (2021) to check whether the variables have the issue of cross-sectional dependence (CD). The test results are documented in Table 4.

For *mp, reic*, and *y* all three tests performed reject the null hypothesis of weak CD effect in favor of the alternative hypothesis of strong CD effect. For *pr* only two out of three tests reject the null hypothesis. Overall, the test results suggest that the variables, particularly our main variables of interest – i.e., *mp* and *reic* – are cross-sectionally dependent. Statistically, the key message from these results is that for checking unit root and cointegration properties of the variables, as well as for estimating *mp* equation in (2.3), we need to use methods that account for CD effect.

Table 5 documents the results of the panel unit root tests developed by Pesaran (2007), which is the second-generation test accounting for CD effect.

The table indicates that the cross-sectionally augmented Im-Pesaran-Shin (CIPS) test by Pesaran (2007) decisively suggests unit root process in the form of integrated order of one, i.e., I(1) for all the variables except for *pr*. This is because none of the sample Z statistics in the table from the test of the levels of the variables is greater than the critical values in absolute terms (see the second column). Hence, the null hypothesis of the unit root cannot be rejected for all variables. However, the sample Z statistics are greater than the critical values from the test of the first difference of the levels, which lead to the rejection of the null hypothesis, except for *pr* (see the third column). These results are satisfactory enough to conclude that the log level of the variables, i.e., *mp*, *reic*, and *y* are unit root processes. Regarding *pr*, we tested the second difference of it, that is, *d2_pr*. The test sample statistic is much greater than the critical value. This suggests stationarity of the second difference of *pr* meaning that *pr* is a second order difference stationary variable, i.e., I(2) process. Thus, the implication of the unit root test results is that in the long-run analysis, such as cointegration test and estimation, *mp*, *reic*, *y*, and first difference of *pr*, *d_pr*, should be used. While in the short-run analysis, the first difference of the other variables and the second difference of *pr*, that is, *d_mp*, *d_reic*, *d_y*, and *d2_pr* should be considered.

Since we found the variables to be non-stationary in their levels, it gives good reason to think that they may establish a long-run relationship. If this is the case, then we will be interested in estimating numerical parameters of this long-run relationship for *mp*. To check whether variables establish the long-run relationship, we use the Westerlund (2007) cointegration test with bootstrapping to account for the CD effect. The results are recorded in Table 6.

The Westerlund (2007) test statistics, Ga, Pt and Pa, with bootstrapping confirm the existence of cointegration among the variables. It is well-known that Westerlund (2007) test statistics under-reject the null hypothesis if data span is small like our case here, as he discusses (Westerlund 2007). Given that, it is very promising that three out of four test statistics indicate a co-integrating relation among the variables, even though we have a small sample span. In conclusion, the variables under consideration– i.e., *mp*, *reic*, *y*, and *d_pr* – are cointegrated. Put differently, *mp* may establish a long-run relationship with the explanatory variables considered.

Table 4. The results of the CD tests.

Variables	Pesaran (2015)	Fan et al. (2015)	Pesaran and Xie (2021)
mp	27.93***	185.84***	–1.73*
reic	32.18***	213.83***	–3.60***
y	20.22***	100.80***	1.64*
pr	20.24***	144.66***	0.54

Notes: **, **, and *** indicate rejection of the null hypothesis of weak CD in favor of the alternative hypothesis of strong CD at the 1%, 5%, and 10% significance levels, respectively.*

Table 5. The results of the Pesaran (2007) panel unit root test.

Variables	Level	First difference	Second difference
	CIPS	CIPS	
mp	0.239 (0.594)	–6.033 (0.000) ***	
reic	–0.378 (0.353)	–3.573 (0.000) ***	
y	–0.293 (0.385)	–3.839 (0.000) ***	
pr	–0.967 (0.167)	–0.551 (0.291)	–7.597 (0.000) ***

Notes: **, **, and *** indicate rejection of the null hypothesis of unit root in favor of the alternative hypothesis of (trend) stationarity at the 10%, 5%, and 1% significance levels, respectively. The values in the table are the Z statistics from the cross-sectionally augmented Im-Pesaran-Shin (CIPS) test by Pesaran (2007) and values in the parentheses are the associated probabilities. The CIPS test assumes cross-section dependence in the form of a single unobserved common factor. The test equation includes intercept and time trend in testing the level of the variables while they include intercept only for the testing the first (or second) difference of the levels. This is based on the statistical significance of the mentioned deterministic regressors. The lag order of one is selected to remove serial correlation from the residuals of the test equation.*

Table 6. The results of the Westerlund (2007) panel cointegration test.

Statistics	Gt	Ga	Pt	Pa
Sample value	–1.794	–8.989**	–7.189**	–12.393***
p-values	0.300	0.025	0.013	0.000

Notes*: *, **, and *** indicate rejection of the null hypothesis of no cointegration in favor of the alternative hypothesis of cointegration at the 10%, 5%, and 1% significance levels, respectively. Westerlund (2007) cointegration tests were performed without intercept and trend, as this was dictated by the statistical insignificance of the deterministic components in the test equations. To address the CD effect and get robust probability values, the test is run with bootstrap (80 values).*

Table 7. The polled long-run estimation results for the panel of seven countries.

Regressor	*Constant*	d_pr_{it}	y_{it}	$reic_{it}$
	14.519*	–1.028**	0.660	0.195***
	(0.125)	(0.068)	(0.430)	(0.037)

Notes: *Dependent variables is mp_{it}. *, **, ***, and **** indicate rejection of the null hypothesis of no statistical significance at the 16%, 10%, 5% and 1% significance levels, respectively. Numbers in the parentheses are the associated probabilities. Exclusion of the time trend in the estimations was because of its statistical insignificance. Number of observations = 27 (Time series observations) × 7 (Number of countries) = 189.*

As mentioned above, finding a cointegrating relation among the variables gives ground to estimate equation (2.3) for *mp*, which would provide us with its long-run elasticities with respect to the explanatory variables. We used the CCE MG as a method for estimating the long-run elasticities. The impact of renewable energy on petrochemicals import is our main interest in this study. Therefore, we report its impact both for a pool of countries (in Table 7) and for each individual country in the pool (in Table 8). The effects of the relative prices and income, on the other hand, are only reported at the pooled level.

In determining the statistical significance of the estimated coefficients, we consider a threshold of up to 16% due to the small number of observations. Note that considering 16% of significance level is in line with the empirical studies conducted by seminal econometricians, including David Hendry, James Stock, and Lutz Kilian (see Castle, Doornik, and Hendry 2021; Metcalf and Stock 2020; Kilian 2009; Kilian and Park 2009). Note that our main variable of interest, $reic_{it}$ remains statistically significant at the 5% level. Moreover, the relative prices variable is statistically significant at the 10% level with the theoretically expected negative sign. The Income variable also takes the theoretically expected sign, which is positive, although it is not statistically significant. If we exclude it from the estimation, we still get positive and more statistically significant impact of $reic_{it}$,` our variable of interest, being 0.173 with the probability of 0.008. *Constant* is statistically significant at 16%. Even if it is statistically insignificant, we would not exclude it from the estimation because it is hard to assume that the initial level of mp_{it} is zero. Thus, we prefer to stick with the estimation results of equation (2.3) as it retains theoretically articulated factors, namely income and relative prices, in which our variable of interest is statistically significant with the expected positive sign. Table 8 presents the country-specific long-run elasticities of petrochemicals import with respect to renewable energy installed capacity estimated from equation (2.3) for each individual country.

The main takeaway from the table is that the impact of $reic_t$ on mp_t is positive for all countries at the different levels of statistical significance; none of them is negative.

For Brazil, the impact of $reic_t$ on mp_t initially was negative 0.060 with the p-value of 0.788 from the standard PMG estimation. As discussed in the data section, Brazil is ranked third in terms of installed capacities of solar panels and wind turbines. In addition, the graph for Brazil in Figure 1 illustrates that $reic_t$ and mp_t co-move with an upward trend over time. Hence, obtaining a negative coefficient would cast some doubt. Thus, we further investigate Brazil to make sure that the obtained estimate is an accurate representation of the impact of $reic_t$ on mp_t and is not the result of a data complication. In this regard, one should have a good reason to suspect that the estimation results for Brazil might be distorted by the huge drops in the time trajectory of mp_t in 2008 and 2022. Numerically speaking, mp_t dropped as much as 31% and 32% in 2008 and 2022 relative to the previous years, respectively. These drops in the mp_t series were not captured in the panel estimation. Therefore, we re-estimated the ARDL equation for Brazil by accounting for these huge drops using two dummy variables. All the post-estimation and cointegration test results are acceptable.[10] The estimation yields the long-run elasticity of mp_t with respect to d_pr_{it}, y_{it}, and $reic_{it}$ to be –0.167, 2.566, and 0.178 with the probability values of 0.042, 0.000, and 0.000, i.e., all three being statistically significant. If we replace these

Table 8. Country-specific long-run elasticities of installed renewable capacity.

Country	$reic_t$	*P-value*
Brazil	0.178****	(0.000)
Chile	0.047	(0.724)
China	0.610**	(0.064)
India	0.452	(0.224)
Mexico	0.086*	(0.134)
Thailand	0.021	(0.377)
Turkey	0.211***	(0.030)
Slope Heterogeneity Test:		
Adjusted test value: 4.773**** (0.000)		

Notes: *Dependent variable is mp_t. P-values are in parentheses. *, **, ***, and **** indicate rejection of the null hypothesis of no statistical significance at the 16%, 10%, 5%, and 1% significance levels, respectively. T=27. Exclusion of the time trend from the estimations was because of its statistical insignificance. We did not exclude constant if it is statistically insignificant because it is hard to assume that MP initial level is zero.*

elasticities above with the ones estimated from the standard PMG for Brazil, then the panel elasticities for the pool of seven countries reported in Table 7 will change to **−0.858**, **1.043**, and **0.229** for d_pr_{it}, y_{it}, and $reic_{it}$, respectively.

Robustness Check for the Estimated Positive Impact of Renewables on Petrochemicals

We estimated a positive impact of renewables on demand for petrochemicals' import from equation (2.3) as reported in Table 7. Moreover, each country-specific estimation reported in Table 8 demonstrates the positive impact of renewables. Econometrically, this is a multiple regression, in which an estimation of the coefficient of a regressor involves variance and covariance of the other regressors in the equation as well (e.g., see Gujarati and Porter 2009, Chapter 7). Given that income elasticity of the petrochemicals' import demand was statistically insignificant in the estimation of equation (2.3.), one can be interested in exploring what would happen to the estimate of renewables elasticity if the equation were estimated without income variable in it; in other words, whether the impact of renewables on petrochemicals' import demand will still preserve its robustness by becoming positive and statistically significant coefficient. As a further robustness, one can challenge the renewables' impact by estimating various modifications of equation (2.3). To this end, we considered all possible relevant reduced forms of equation (2.3) by excluding regressors. This yielded the following four specifications: (i) without income; (ii) without relative prices; (iii) without income and relative prices; (iv) without renewables.[11] Table 9 reports the estimation results.

The key takeaway from the table, with respect to our focus, is that renewables consistently exhibit positive and statistically significant elasticities across all three specifications, from Model 1 to Model 3. Two other notable findings are as follows. First, none of the estimations from these four specifications outperform theoretically and statistically those from equation (2.3) in Table 7z, which was our preferred specification. This finding reaffirms our choice even though the income elasticity is statistically insignificant. Second, the standard import demand model, that is, equation (2.3) without renewables in Model 4 does not yield any superior results compared to our preferred

Table 9. The long-run estimation results from reduced forms of equation (2.3).

Regressor	C_{it}	d_pr_{it}	y_{it}	$reic_{it}$
Model 1	2.662**** (0.004)	−0.500 (0.678)	—	0.173**** (0.008)
Model 2	20.122*** (0.004)	—	0.697 (0.263)	0.165*** (0.046)
Model 3	2.611**** (0.004)	—	—	0.200*** (0.024)
Model 4	−5.470 (0.591)	−0.167 (0.913)	0.508 (0.425)	—

Notes: *Dependent variables is mp_{it}. C_{it} is the country specific intercept *, **, *** and **** indicate rejection of the null hypothesis of no statistical significance at the 16%, 10%, 5% and 1% significance levels, respectively. Numbers in the parentheses are the associated probabilities.*

Equation (2.3): $mp_{it} = a_{0i} + a_{1i} d_pr_{it} + a_{2i} y_{it} + a_{3i} reic_{it} + v_{it}$

Model 1: Equation (2.3) without y_{it};

Model 2: Equation (2.3) without d_pr_{it};

Model 3: Equation (2.3) without y_{it} and d_pr_{it};

Model 4: Equation (2.3) without $reic_{it}$.

Exclusion of the time trend in the estimations was based on its statistical significance. We did not exclude constant if it was statistically insignificant because it is hard to assume that the MP initial level is zero. Number of observations = 27 (Time series observations) × 7 (Number of countries) = 189.

specification, i.e., equation (2.3), where renewables are included. In contrast, the impact of relative prices is largely statistically insignificant in Model 4, whereas it is statistically significant in Table 7. This suggests that augmenting equation (2.1), that is, the theoretical import demand model with renewables, was a reasonable strategy, which is in line with suggestions of combining theory-driven and data-driven approaches as discussed in Section 2.

In summary, the conducted robustness check here demonstrates that the positive impact of renewables on petrochemicals remains if various specifications are considered.

6. Discussion of the Results

According to Table 4, the variables under consideration are correlated across the countries in our sample. This cross-country correlation or dependence can occur due to common factors affecting these countries. Such factors may include globalization, the international spillover of technologies and efficiency measures as developing economies strive to catch up with advanced economies, international economic linkages like trade and capital flows, global price movements, widespread shocks and recessions, and climate change-related policies and measures (see discussions in Bai, Baltagi, and Pesaran 2016; Pesaran 2015b, chapter 29; Baltagi and Pesaran 2007).

The unit root process, i.e., non-stationarity, suggests that the variables are continuously drifting over time and do not return to their previous sample mean as the mean value itself changes. Any disturbance or shock to such drifting variables can have a lasting impact. Predicting future values of these variables is challenging due to the changing average and the permanent effects of shocks. For prediction purposes, it is advisable to use a stationary transformation of the variables to overcome this issue. Stationary series have relatively stable mean, variance, and covariance over time, and they fluctuate around their mean values. These stationary series are known as mean-reverting processes because they tend to revert to their mean values.

From the cointegration test results, we found that imports of petrochemicals have a long-run relationship with renewable energy, relative prices, and income. In other words, petrochemical imports share a common trend with these factors, and they move together, establishing an equilibrium relationship in the long run. Another interpretation of cointegration is that the relationship among (the logarithmic levels of) the variables is not a chance occurrence, i.e., spurious, rather it aligns with economic thinking. Consequently, the estimated long-run coefficients can be used for analysis and projections.

We estimated the long-run impacts of the renewable energy, relative prices, and income on petrochemical imports for the pool of countries as well as for each country. Since the renewable energy is our main variable of interest in this study, we discuss its impact on petrochemical imports both for a pool of countries and for each individual country, whereas the impacts of the relative prices and income are discussed at the pooled level only.

Table 7 shows that for the panel of the countries, a **1%** increase in renewable energy installed capacity increases petrochemical imports by **0.2%** in the long run, keeping other factors unchanged. Turning to the country specific results reported in Table 8, the first observation is that the elasticity of petrochemical imports with respect to renewable energy installed capacity is positive for all seven countries in our sample. This finding shows that expansion in the renewable energy installed capacity can lead to more imports of petrochemicals in 100% of the entire country sample under consideration.

It is conceptually/theoretically expected that an increase in renewable installed capacity requires an increase in its manufacturing, which requires more consumption of petrochemicals such as rubber and plastics. In particular,

the demand for (reinforced) plastic materials, resin, and polymer matrix would increase to produce encapsulant, back-sheet, wind turbine blades (e.g., Korniejenko et al. 2021). Such plastics, which are sourced from chemical and petrochemical substances, can also play a role in the next round of cost reductions in renewable energy generation technology. For example, in the wind energy sector, light-weight plastic-based materials can help address the challenges of making longer turbine blades, thereby increasing generation efficiency. Innovative materials can also help increase the durability of wind turbines, thus reducing the cost of maintenance. This is especially beneficial in harsh environments, such as those offshore or similar remote locations (see e.g., IEA 2018).

There are a number of processing pathways for non-combustion oil demand as feedstock for the petrochemical industry. The most common and existing commercial pathway is via oil products from refineries such as naphtha and liquefied petroleum gas (LPG), and these account for about 17% of current global oil demand. With ethane feedstock from other hydrocarbon liquids (natural gas liquids) included, the number rises to about 22% of the oil demand (IEA 2023). Under various IEA scenarios, global oil demand arising from petrochemical production is projected to be in the range of 50% and 80% of total oil demand by 2050 (IEA 2023). The majority of this demand is expected to emanate from developing and emerging economies where factors such as population growth, rising standard of living, and industrialization would be the drivers.

Moreover, the IEA's projected scenarios for sectoral energy consumption by 2040 pointed out that non-combustion demand for oil – i.e., as a feedstock for petrochemicals and chemicals production – is expected to lead the final energy consumption growth, as the petrochemical sector's demand for feedstocks is forecasted to rise by 41% and 29%, according to the Stated Policies (STEP) and Sustainable Development (SD) scenarios, respectively (WEO 2019).

Thus, as calls for combating climate change propel global energy transition towards higher renewable energy penetration major expansions of the global petrochemicals sector are envisaged.

The estimation results also show that the size of the elasticity varies from the minimum of **0.021** in Thailand to the maximum of **0.610** in China. This reveals differences in the response of petrochemical imports to the renewable energy installed capacity in the countries considered driven by their specificities, although all of them are developing nations. Such specificities include the degree of diversity of applications of petrochemical products in the country, among others. Indeed, one would not expect the response of, say, India to be the same as that of Chile.

Moreover, none of the positive elasticities are greater than unity, that is, they are inelastic, meaning that an increase in the renewable energy installed capacity causes less than the same magnitude of increase in the imports of petrochemicals in the countries considered. Furthermore, the elasticities are statistically significant at the 16% level or higher for 4 of 7 countries, that is, China, Brazil, Mexico, and Turkey, while they are not statistically significant in Chile, India, and Thailand. This might be interpreted that in China, Brazil, Mexico, and Turkey the level of the development of the renewable energy installed capacity is high enough to significantly influence imports of petrochemicals. On the contrary, the level is not high enough in the other countries to make a significant impact.

Table 7 further reports that for the panel of the countries, a **1.0%** fall in petrochemical imports is caused by a **1.0%** increase in the relative prices of international to domestic in the long run. The negative relationship found here is in line with demand theories, including those for imports. When it comes to the magnitude of the impact, the estimated opposite one-to-one relationship between petrochemical imports and the relative prices is due to country characteristics. It shows that these seven countries' petrochemical imports are quite sensitive to changes in petrochemical prices in the domestic and international markets.

Lastly, Table 7 documents that a **1.0%** increase in the income of the countries considered, measured by manufacturing value added, leads to a **0.7%** increase in their demand for petrochemical imports. This finding is consistent with demand theories, although it is not statistically significant at the conventional levels. The statistically insignificant income effect found might imply that petrochemical products are necessary goods for the manufacturing sectors of these countries. Hence, regardless of the level of income, these goods have to be imported to materialize the production process. Such an explanation is supported by previous studies. For example, Guo et al. (2023) found that electric vehicle production increases demand for petrochemicals and hence, oil imports.

Moreover, our finding of the positive impact of the manufacturing sector on (imported) demand for petrochemicals (i.e., plastics and rubber) is also consistent with the findings of other previous studies. They find that a higher demand for petrochemical products such as plastics and rubber is created by manufacturing of automobiles, electrical goods and electronics (Guo et al. 2023; Giannikopoulos et al. 2022), healthcare (IEA 2018), textiles (Halawani and Al Dabbagh 2020), food processing (Raj et al. 2021), and packaging (Mangaraj et al. 2019). As IEA (2018), among others, discusses, petrochemicals are the raw materials/intermediate goods for many manufacturing sectors including but not limited to fertilizers, packaging, food, pharmaceuticals, and automobiles. Thus, the overall demand for petrochemicals is derived from demand for these manufacturing sectors' output. Consequently, the structure of economies can considerably affect demand for petrochemicals. This is especially true for developing and less-developed economies given that structural transformations in these economies are towards industrialization.

Future Opportunities for Petrochemicals in the Renewable Energy Transition

In all IEA energy transition scenarios, solar and wind power systems are expected to account for over 70% of global electricity capacity additions between now and 2050 (WEO 2023). In 2022, global installed wind and solar PV systems were about 2083 GW with wind turbines representing about 43.5% and solar PV accounting for 56.5%. India and China alone accounted for about 43% of the overall global installed wind turbines and solar PV. These two countries are also major sources of import demand for petrochemicals investigated in this paper. According to the IEA Net Zero Emissions Scenario (WEO 2023), global solar PV and wind turbine installed capacities are expected to cumulatively rise to about 18750 GW and 7620 GW by 2050, respectively. Future growths of installed capacities of these energy systems are anticipated to be dominated by China and India as well (WEO 2023).

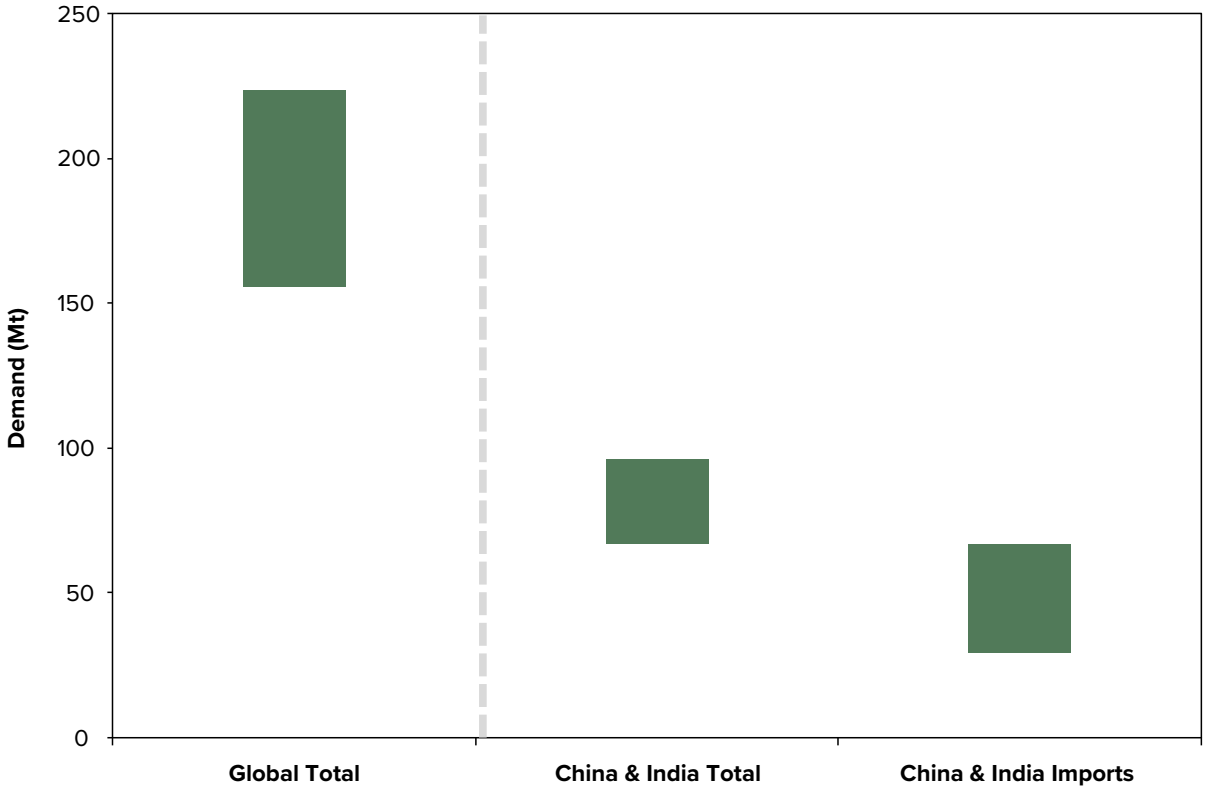
If future capacity additions continue to be dominated by China and India at their current share of 43%, it is possible to evaluate potential opportunities for future petrochemical polymer material import demand in these countries if the historical import dependence is not altered significantly in the anticipated future Net Zero Transition scenario. Furthermore, considering the scale of capacity growth projected for a net-zero future, material composition data can also furnish estimates of the global petrochemical polymer requirements to manufacture these renewable energy systems. Table 10 shows the typical design attributes of solar PV and wind turbine systems, indicating the ranges of values reported by various manufacturers of these systems in their materials specification data sheets.

To quantify the petrochemical polymer demand for these energy systems, it is instructive to take a conservative approach considering the range in values of the design attributes of each system. The design attributes of focus include the unit design capacity, unit weight, and petrochemical polymer composition. Using a cautious approach, estimates of petrochemical polymer demand for the solar photovoltaic and wind turbine systems can be bounded within the range of their minimum and maximum values by applying the upper range value of their respective polymer composition to the lower range value of the unit weight of each of the energy systems. This is a reasonable approach to follow because the systems with higher compositions of petrochemical polymers are more likely to be of lighter weight, though not necessarily of lower capacity than those with lower compositions of the polymers. Light-weighting of wind

Table 10. Design attributes of typical solar PV and wind turbine systems.

	Renewable Energy System		
Attribute	**Solar Photovoltaic**	**Wind Turbine**	**Sources**
Unit design capacity	0.25-0.5 kilowatts	1.5-5.0 megawatts	Latunussa et al. (2016), Dominish et al. (2019), USGS (2018), Rosenbloom (2024).
Unit weight	18.14-34.93 kilograms	150-485 metric tons	
Polymer composition	6.6-10%	11-16%	

Figure 3. Petrochemical polymer demand for energy transition under the NZE scenario.



Source: Author's own construction

turbines in particular is a known measure for energy efficiency performance improvement. Figure 3 presents the results for NZE global demand for petrochemical polymers along with the demand by China and India, and the potential import demand opportunities in both countries.

Depending on the choices of the design types of solar photovoltaic and wind turbine systems deployed globally towards achieving NZE targets by 2050, the total global petrochemical polymer demand required to manufacture those energy systems has been quantified to range between 155 to 223 million metric tons (Mt); this translates to an equivalent crude oil demand of between 0.80 to 1.13 million barrels per day over the period from 2025 to 2050. The lower bound value represents the material requirement if only existing designs of the systems with the lowest content of petrochemical polymers are deployed in the transition, whereas the upper bound value represents the requirement if systems with the highest content of polymers are built. Similarly, China and India alone would require between 67 and 96 Mt of polymer materials for their solar and wind power systems deployments towards the global NZE ambition by 2050.

Using the estimated country-specific elasticities of import demand of petrochemical polymers with respect to annual installed solar and wind power systems capacities in China and India, the import demand of petrochemicals corresponding to the NZE transition scenario capacity additions requirements in both countries is also quantified (right of the dashed line in Figure 3). Consequently, the NZE installed capacity growth requirement of around 1150% entails additional import demand of about 67 Mt by China and India in the transition period from 2022 to 2050.

7. Concluding Remarks and Policy Insights

Many studies considered renewables and hydrocarbons as alternative sources of energy and found an inverse relationship between the two. However, to date there is no dedicated applied research study estimating the impact of renewables (e.g., solar and wind) industry on demand for petrochemicals (e.g., plastics and rubber) using actual data to the best of our knowledge. In this imbalanced context, the prevailing view is that the shift towards renewable energy would diminish the demand for hydrocarbons.

Our study challenges this notion by empirically demonstrating that renewable energy developments could actually have a positive impact on hydrocarbons, driven by their growing demand for petrochemicals. Just the capacity expansion requirements for wind and solar energy systems under the IEA Net Zero scenario entails an increase in crude oil equivalent petrochemical feedstock demand of around 6%. Our primary finding, that renewables positively impact the import demand for petrochemicals, remains robust across various model specifications considered in our empirical analysis.

For policymakers in petrochemical-importing economies, the findings of this study suggest that their transition to renewables may necessitate increased demand for petrochemicals import. Furthermore, developments of domestic manufacturing and high domestic prices of petrochemicals relative to the international prices could additionally boost this import demand. Meanwhile, policymakers in petrochemical-exporting economies should recognize the potential opportunities presented by these findings for expanding petrochemicals and related sectors. This also encompasses hydrocarbon feedstocks such as ethane, propane, butane, and naphtha that are fundamental to the petrochemical industry, and currently, there are no readily available substitutes with better environmental impact, cost-effectiveness, or efficiency for these energy transition technologies.

Endnotes

[1] IRENA Innovation Landscape for Smart Electrification: Power to Heat and Cooling Status.

[2] A downturn in the hydrocarbon sector would result in a decrease in petrochemicals due to the reduced availability of key feedstocks such as ethane, liquefied petroleum gases (LPG), naphtha, and methane. Additionally, due to complexity and other challenges, alternative green feedstocks are not yet produced at sufficient levels to offset any decline in hydrocarbon-based feedstocks (Kelly & Hart 2023; IEA 2018).

[3] Another opportunity might be the demand for petrochemicals in electric vehicle production (Guo et al. 2023; Buchard & Junkers 2022). Increasing demand for electric vehicles is projected to accelerate the need for petrochemicals, such as rubber and plastic products (e.g., WEO 2019; IEA 2018). Since this channel does not directly link renewable energy to petrochemicals, it might be found to be somewhat arguable. Consequently, we do not consider it in this present work.

[4] The share of green feedstock such as biorefinery in total feedstock for petrochemical is quite small due to its given complexity and other challenges (e.g., see Kelly & Hart 2023; IEA 2018).

[5] Note that Giannikopoulos et al. (2022) simulated the impact of electric vehicles on the US petrochemical sector. However, this research explores the petroleum refining industry and petrochemicals effects of vehicles, running on renewably generated electricity, but not the effect of renewable energy production or installed capacity. Additionally, that is a simulation analysis using an optimization-based model not a behavioral analysis quantifying the impact by applying econometric method(s) to actual data.

[6] Our forthcoming study will examine the same topic for the developed countries.

[7] https://www.statista.com/statistics/668749/regional-distribution-of-solar-pv-module-manufacturing/#:~:text =China dominates the solar industry, leader in installed PV capacity.

[8] https://www.blackridgeresearch.com/blog/top-wind-turbine-manufacturers-makers-companies-suppliers.

[9] Initially, we also had Poland, Romania, and Czechia in our sample, and an empirical analysis was conducted considering these 10 countries in the previous version of this paper. In the current version of the paper, we have excluded these three countries following a referee's suggestion expressing that they are classified as developed countries for the second half of the time sample of this study (see the United Nations World Economic Situation and Prospects reports).

[10] The ARDL(1,1,0,0) final specification was selected by the Akaike Information Criterion from the ARDL(1,1,1,1) general specification for the mpit equation with the regressors d_prit, yit, and reicit. The null hypotheses of no autocorrelation, no serial correlation, normality, and homoscedasticity cannot be rejected at conventional significance levels. Additionally, the Bounds test indicates cointegration among the variables, as the sample F-value of 8.74 exceeds the critical upper bound F-value of 5.966 for 30 observations with an intercept included in the long-run equation.

[11] By "relevant" we mean specifications that include renewable energy installed capacity and a standard import demand specification, incorporating only income and relative prices.

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Notes

Acknowledgments

We would like to thank the participants of the third ERF GCC Conference – GCC Economies in an Era of Energy Transition. Particularly, our gratitude goes to Omar Al-Ubaydli for his valuable comments. We also thank Andrea Bollino, Walid Matar, and Olivier Durand-Lasserve for their comments and suggestions. The views expressed in this paper are those of the authors and do not necessarily represent the views of their affiliated institutions. We are responsible for any errors and omissions.

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About the Project

This study is part of the KGEMM Policy and Research Studies project, which produces policy and applied research to help Saudi Arabian decision-makers better understand domestic and international macroeconomic-energy relationships. The project primarily uses KGEMM, an energy- and emissions-sector augmented macro-econometric model, along with partial equilibrium frameworks.



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