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An Assessment of India's Energy Choices: What it Means for the Economy, Jobs, and Energy Security

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About the Series: An Assessment of India's Energy Choices

This report is part of a four-report series that looks at the future of renewable energy in India along different economic dimensions. The four reports in the series are:

Social Costs of Coal-Based Electricity in India: Estimates of Impact on Health and Agriculture
Ashwini Chhatre, Indian School of Business

What it Means for the Economy, Jobs, and Energy Security
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An Assessment of India's Energy Choices: What it Means for the Economy, Jobs, and Energy Security

India's economy is growing rapidly, and with it, so is energy demand. The IEA-IEO (2015) estimates that India's aggregate energy consumption will more than double by 2040.

The growing demand for energy has raised two major concerns. First, in the absence of stringent policies to mitigate energy-related emissions of gases, dust, and fumes from the power sector, industry, and transport, India's air pollution problems loom large. Second, dependence on imports of conventional energy like coal, oil, natural gas has posed a threat to India's energy security. With substantial potential for growth in per capita energy consumption as well as emphasis on enhancing overall energy access, these issues are likely to get worse.

Facing these dual issues, it will be important for India to adopt policies that enhance indigenous energy production as well as encourage the use of alternative, sustainable, and decentralized sources of energy, such as solar and wind. The Government of India has an ambitious goal to achieve 175 GW of renewable energy by 2022, which would amount to around 18.9% of aggregate renewable energy power consumption in India in 2022.

As India works to meet this target, it is important to explore the relationship between renewable energy penetration and key macroeconomic factors such as GDP, the fiscal deficit, energy imports, employment, capital returns, and population, to ensure that multiple national priorities are achieved simultaneously.

This paper, produced by Jawaharlal Nehru University and the Indian Institute of Technology is part of a four-part series led by Climate Policy Initiative for Shakti Sustainable Energy Foundation that looks at paths to renewable energy penetration in India along different dimensions including the social costs, macroeconomic impacts, environmental impacts, financial risk, and flexibility considerations.

This particular analysis takes on macroeconomic impacts of India's renewable energy pathway.[1] By establishing the relationship – negative, positive, or neutral – between key macroeconomic factors and renewable energy, we gain insight into whether India can meet economic and clean energy targets simultaneously. Using the model developed in this exercise, we then project three scenarios – a business as usual, optimistic, and pessimistic scenario - to forecast different levels of renewable energy penetration in India's energy economy.

We find that renewable energy is clearly associated with positive impacts for India's economy including the potential to add up to 4.5 million domestic jobs by 2042 under an optimistic, but realistic, scenario. However, we also find that despite these benefits, under the same optimistic scenario, India will not be able to reach its renewable energy targets by 2022, and, in fact, would reach less than half the 175 GW target by that date.

The key results and takeaways around the relationship between macroeconomic factors and renewable energy from this analysis are as follows:

- **As India's Gross Domestic Product (GDP) grows, so does renewable energy generation.** This implies that higher incomes induce a higher willingness to pay for renewable energy or a higher demand for renewable energy. This could also be because renewable energy is a normal good, meaning cleaner energy is demanded more at higher incomes or people shift their energy preferences from conventional fossil energy to cleaner energy with an increase in income levels.

- **As renewable energy generation increases, the fiscal deficit decreases, and vice versa.** A higher fiscal deficit is largely indicative of higher financial support to fossil energy generation. Therefore, a higher level of

1 Our analysis utilizes macro-econometrics and time series methods for these estimations. These include tests of stationarity, Granger causality tests and co-integration using an autoregressive distributed lag (ARDL) model structure.

renewable energy penetration is associated with lower fiscal deficit on account of a lower share of fossil energy generation. A policy implication, therefore, is to increase renewable energy penetration, in order to reduce the fiscal deficit.

• **Increased renewable energy generation is correlated to fewer net energy imports.** Energy imports largely consist of fossil energy. Thus, renewable energy substitutes for fossil energy in the aggregate, which, in turn, reduces net energy imports. A policy implication, therefore, is to increase renewable energy generation in order to reduce net energy imports, which assert a huge drain on the Indian economy.

• **Higher renewable energy generation corresponds to lower unemployment.** A policy implication, therefore, is to increase renewable energy generation, in order to increase employment and jobs.

• **Renewable energy generation growth is correlated to higher interest rates.** In general, a higher interest rate constitutes either a higher cost of capital (which may dampen investment in renewable energy) or a higher return on capital investment (which encourages investment in renewable energy equipment). At the macro-level, the latter effect appears to outweigh the former. This is quite an interesting finding, given that it does not support the hypothesis that a reduced cost of capital would reduce the cost of renewable energy, thus making it more competitive. This may require further investigation.

• **Interestingly, the higher India's population, and the larger the percentage of that population with access to energy, the less renewable energy generation, and vice versa.** Intuitively, a higher population level or higher access of population to electricity places heavy demand on the economy in terms of demand for energy. However, our model shows the opposite. This is quite an interesting finding, given that it does not support the hypothesis that renewable energy can help improve energy access. However, this may be due to the limited time series dataset (for 27 years only) and India's excessive dependence on fossil energy to-date; this may undergo a change as more renewable energy diffusion happens.

Based on these economic indicators, we project three scenarios for India's renewable energy penetration.

Notably, our estimates show that in order to meet India's clean energy and growth goals we need to focus more on strong renewable energy policies, and also on strong macroeconomic policies. Specifically, we find that the 175 GW target is likely to be achieved during 2029-30 under the business as usual scenario, a bit earlier, in 2027-28 under the optimistic scenario, and a lot later, in 2032-33 in the pessimistic scenario. This is in consonance with the recent apprehensions expressed in this regard, especially given the available policy framework moving away from feed-in-tariffs to auctions-based purchases, lack of grid infrastructure, and evacuation constraints (Live Mint 2017).

We find that under the optimist scenario, India would add 4.5 million renewable energy jobs by 2042. Using shares across different renewable energy technologies unchanged over the years of forecasting, and relying on norms of job creation for these technologies, we obtain the following direct incremental job generation potential for India in 2022 (CEEW-NRDC, 2017): 251,000, 286,000, and 311,000 in pessimistic, business as usual, and optimistic scenarios respectively. In 2032, these are expected to rise to 978,000, 1.4 million, and 1.5 million respectively under the three cases. And finally, in 2042, these are expected to rise to 2.05 million, 3.98 million, and 4.52 million jobs.[2]

Table ES1: Renewable energy values under three realistic scenarios

Values	Year	Pessimistic scenario	Business as usual scenario	Optimistic scenario
Renewable energy (MTOE)	2022	14.71	15.56	16.13
	2032	31.93	42.15	45.08
	2042	57.44	103.16	115.83
Renewable energy capacity installed at 25% plant utilization (GW)	2022	78	83	86
	2032	170	224	239
	2042	305	548	615[3]
Share of renewable energy generation in primer energy supply (%)	2022	1.38	1.42	1.45
	2032	2.12	2.75	2.86
	2042	2.9	5.15	5.74

2 We have assessed the contribution of renewable energy to job creation potential using renewable energy sector specific data. This is subject to the proviso that these numbers may not necessarily be incremental. For a more accurate estimate, a more extensive, economy wide general equilibrium analysis is required.

3 The estimate for the year 2040 is 510 GW, which is closer to the estimates by the NITI Aayog.

Our findings show that India's energy security increases significantly under all three scenarios. To discern the future of energy security for India, we compute the energy security index (ESI) for India under alternative scenarios[4]. The ESI is normalized in a manner as to lie within the range of 0 and 1. A value closer to 1 denotes a higher level of energy security, while a value closer to 0 implies lower energy security. We calculate that India's ESI is currently 0.41, which is on the lower side. It is highest in the optimistic scenario, where it reaches 0.44 in year 2022 and 0.58 (a moderate value) by 2042, a more than 40% improvement. However, we also find that energy security does not vary too much across the scenarios.

Policy implications

Based on our analysis we find that renewable energy penetration in India is positively associated with important economic growth indicators including GDP, employment, and energy security, and therefore, additional renewable energy is consistent with strong growth targets.

We also find that a higher economic growth rate, a higher return on investment, and a more remunerative renewable energy tariff is likely to spur renewable energy growth. Alternatively, a higher fiscal deficit, and higher energy imports will dampen renewable energy diffusion.

India can therefore take steps to meet both clean energy and growth goals by focusing not only on strong renewable energy policies, but also on strong macroeconomic policies.

4 We compute a comprehensive index of energy security by relying on several indicators of energy security, namely, market liquidity, share of renewable energy generation in total primary energy supply, net energy imports to total primary energy supply ratio, Herfindahl-Hirschman market index of energy imports to India, percentage of population with access to energy and energy outlay.

Table of Contents

List of Figures

List of Tables

Technical Report: Summary

In view of energy being a crucial input for the growth and development of an economy, both fossil energy (FE) and renewable energy (RE) have strong backward and forward linkages with key factors characterizing the macroeconomy, demographics and the energy economy of India. In view of the ambitious RE targets that India has set to achieve over the next five years or so, it is important to examine rigorously the role that RE will play in terms of its interaction with key variables that include GDP, population, fiscal deficit, capital borrowing and lending rates (indicative of return on capital investment), energy import dependence, energy access (rural electrification and access to clean fuels), employment etc. The implications of RE penetration on energy security will also provide important insights into how it can contribute toward a more resilient energy economy for India.

We utilize macro-econometrics and time series methods for these analyses. These include tests of stationarity, Granger causality tests and a cointegration exercise using Auto Regressive Distributed Lag (ARDL) model structure for our estimation. The contribution of RE to the job creation potential is assessed in this study using NRDC-CEEW data. For preparing the energy security index, a set of energy security indicators or dimensions are considered, and a distance-function approach is utilized.

The ARDL model estimation points toward an equilibrium cointegrating long-run relationship between RE and key economic variables. The long-run levels of GDP_CONS_01, CALL_RATE and RE_TO_FE_TARIFF are found to be positively associated with the penetration of RE(RE_02), while variables such as FIS_DEF, NET_EN_IMP, POP, POP_ACCESS_PERCENT and UNEMP display a negative relationship with RE(RE_02), penetration in India. These would entail significant policy implications, such as a higher economic growth rate, a higher return on investment, and more remunerative RE tariff would spur RE growth. Alternatively, a higher fiscal deficit, and energy imports will dampen RE diffusion. Similarly, on grounds of policy implications for India, a case can be made for the fact that a higher level of population, or higher share of population in terms of energy access will imply greater reliance on FE rather than RE.

Utilizing the ARDL estimated equation in (1), three different scenarios, namely, business as usual (BAU), pessimistic and optimistic are postulated for forecasting different levels of RE penetration in India's energy economy. The forecasts of RE generation and associated RE capacity are made for the years 2017-2042, for each of the three scenarios. The three scenarios constructed are derived from alternative official trends or policy-targets having implications on key macro variables projected for the Indian economy.

The growth of RE_02 is found to be the highest under the optimistic (OPT) scenario reaching a value of over 16.13 MTOE in 2022, 45.08 MTOE in 2032 and 115.83 MTOE in 2042. The corresponding capacity levels for RE_02, by assuming plant capacity utilization of 25%, are found to be 86 GW in 2022, 239 GW in 2032 and a whopping 615 GW in 2042. The estimate for the year 2040 is 510 GW, which is closer to the estimates by the NITI Aayog. The share of energy supplied by RE_02 to TPES_01 is found to increase from the prevailing less than 1% to 1.45% in 2022, 2.86% in 2032 and 5.74% in 2042.

The growth under the BAU is closer to that in OPT in the initial years, but the gap widens over time. RE generation is estimated at a slightly lower level of 15.56 MTOE in 2022, 42.15

MTOE in 2032 and 103.16 MTOE in 2042. This amounts to a capacity requirement of 83 GW, 224 GW and 548 GW in the respective years, based on the same plant utilization factor values of 25%. Moreover, this amounts to a share of RE_02 to TPES_01 (in MTOE) of 1.42% in 2022, 2.75% in 2032 and 5.15% in 2042.

Under the pessimistic (PES) case, the growth of RE_02 is much slower, both in terms of the energy supplied and capacity installed, as compared to BAU and OPT. It reaches an energy level of 14.71 MTOE in 2022, 31.93 MTOE in 2032 and merely 57.44 MTOE in 2042. The associated capacity installed, assuming the same levels of plant capacity utilization values, will be 78 GW, 170 GW and 305 GW in 2022, 2032 and 2042 respectively. Accordingly, it is estimated, that the share of RE_02 to TPES_01 will be lower at 1.38% in 2022, 2.12% in 2032 and 2.9% in 2042.

The incremental jobs by 2022 amount to 286 thousand, 311 thousand and 251 thousand in BAU, OPT and PES scenarios. In 2032, these are expected to rise to 1409 thousand, 1533 thousand and 978 thousand respectively under the three cases. In 2042, the cumulative job creation levels rise to 3985 thousand, 4520 thousand and 2054 thousand in case of BAU, OPT and PES respectively. These findings are useful to policymakers in indicating the employment potential of RE generation, subject to the proviso that these numbers may not necessarily be incremental. For the latter, a more extensive, economywide general equilibrium analysis is required.

With the inclusion of 6 dimensions, the comprehensive energy security index (ESI) is found to monotonically rise under each scenario. The values are the highest in the case of the Optimistic scenario, followed by the BAU case and the Pessimistic scenario. In the year 2022, ESI is approximately 0.44, under the BAU and the Optimistic scenarios. In comparison, it is a bit lower, at 0.43, under the Pessimistic scenario. The trend is similar in 2032 and 2042 under each scenario, with the values remaining in a tight band of around 0.57 in 2042 in the Pessimistic case, while a slightly higher value of 0.58 is found for the BAU and Optimistic cases in this year.

In the case of 5 dimensions, the ESI rises from 0.48 in 2022 to 0.52 in 2042 under the Optimistic scenario. In the year 2042, as earlier, the value is approximately the same under both BAU and Optimistic scenarios. It is somewhat lower, at 0.51, in the case of the Pessimistic scenario. The rise is ESI is steeper in the case of the Optimistic scenario as compared to the other scenarios.

This aspect of the research provides a comprehensive viewpoint to the policymakers as to how India's energy security varies in terms of RE shares, other macro-economic variables, energy trade characteristics and energy access under the different specifications of these variables. This would provide signal on how appropriate policies to make India more energy secure in terms of RE can be implemented.

1. Introduction and background

1.1 Energy sector in India: now and in the future

Today, India registers itself as one of the fastest growing economies in the world, with an expected annual gross domestic product (GDP) growth rate of 7.6% (at constant 2011-12 prices). With a target of 8% growth per annum in the twelfth five-year plan (2012-17), as well as significant policy initiatives to fillip faster growth for the next 40 years, India's energy needs cannot be overlooked (MOSPI, 2017). Energy being a vital input to the production and consumption processes, it is pertinent that its uninterrupted supply to each of the sectors of the economy is ensured to meet their growing energy demands.

Even though the literature on the determinants of economic growth has primarily dealt with labor and capital inputs, the role of energy as a factor of production cannot be undermined, given that every production process is characterized by transformation of matter which requires energy (Stern 1997). The relevance of energy as an input to economic growth also emerges from the growth hypothesis (Stern 1993, 2000; Lee and Chang, 2005) as well as the feedback hypothesis (Glasure 2002; Erdal et al. 2008) prevalent in the literature on the energy-growth nexus. While the feedback hypothesis states that there exists a bi-directional relationship between energy consumption and economic growth, causality may also run from energy consumption to economic growth, which is termed as the growth hypothesis.

Currently, India accounts for nearly 18% of the world population, yet comprises a mere 6% of global energy demand. While India's energy consumption nearly doubled between the period 2000-15, its per capita energy demand remains low, around one-third of the world average, and much below the levels reached by the United States of America (USA) and European Union (EU). Moreover, a large mass of population in India continues to remain without access to modern and reliable energy sources, with an estimated 240 million without access to electricity (IEA/ IEO, 2015). Herein lies the potential for India's energy economy to grow in the years to come.

India's energy consumption is slated to rise rapidly in the years ahead. According to India's Energy Outlook, 2015, published by the International Energy Agency, some of these trends are quite staggering (IEA/ IEO, 2015). India's total energy demand is expected to be propelled upwards by the year 2040 because of an economic size that would grow to more than five-times its current level in terms of aggregate GDP, and a population growth rate that would make it the country with the largest population. Accordingly, IEO/ IEA, 2015 projects India's aggregate energy consumption to more than double by 2040, with stupendous rise in the offtake of coal, oil and natural gas, often registering it as among the highest energy consumption growth countries across the globe.

Specifically, the power sector will continue to be pivotal to India's future energy economy. With the expected installed power capacity rising from below 300 giga watts (GW) today to over 1000 GW in 2040, albeit coal-fired generation will play a key role (mostly at higher thermal efficiency), led by solar and wind power, the rapid growth in renewable energy (RE), together with increases in nuclear capacity, would imply that these sources would account for over 50% of the new capacity addition between now and 2040 (IEA/ IEO, 2015).

The growing demand for energy has raised two relevant questions: those pertaining to environmental sustainability and those of energy security. In the absence of stringent policies to mitigate energy-related emissions of gases, dust and fumes from the power sector, industry and transport, India's air pollution problems loom large. The dependence on conventional sources of energy, like coal, oil, and natural gas, has posed a threat to environmental sustainability, at both local and global levels. The combustion of fossil fuels releases carbon dioxide (CO_2), sulphur oxides (SO_x), nitrogen oxides (NO_x) and particulate matter (PM), contributing to outdoor and indoor air pollution, global warming and climate change. India recorded 2238 million tons of CO_2 emissions in the year 2014, which is much higher than the 2000 level of 1032 million tons (World Bank, WDI). As countries negotiate to strike a deal in compliance with the Paris Agreement, the voluntary pledges to reduce emissions may translate into a compromise with economic growth on account of the trade-off between the two. In terms of local pollution, the mean annual exposure to particulate matter 2.5 (PM2.5) ambient air pollution concentration in India in 2015 stood at 74.3 micrograms/ cubic meter, much higher than the world average of 44 micrograms/ cubic meter, and way above the average for high income countries of 16.6 micrograms/ cubic meter (World Bank, WDI).

With its significant dependence on imports of energy and substantial potential for growth in per capita consumption as well as overall energy access, India's faces the challenge of placating its energy security concerns. The net energy import dependence for India has risen from 31% in 2000 to 47% in 2015, with little change in the diversity of supply sources (IEA Statistics). The projections under the New Policy Scenario of India's Energy Outlook, 2015, show that India is likely to be in the center-stage of the global energy scene, accounting for a quarter of the increment in global energy use up to 2040, which is more than that for any other country, and amounts to the largest incremental increase in both coal and oil consumption. Concomitantly, India would become a key player in RE generation, with the second-largest solar market in the world. India's increasing reliance on imported energy – especially oil -- would have profound implications for India's energy security, with overall energy import dependence rising to 90% in 2040 (amounting to around 9.3 million barrels/day in 2040) (IEO/IEA, 2015). This raises concerns for India's energy security and socio-economic health of the economy. Consequently, the adoption of tailor-made policies, which are aimed to enhance indigenous production as well as encouraging the use of alternative and sustainable sources of energy, such as solar and wind, is imminent. Apparently, the recent policy push toward renewables and indigenous production of energy substantiate an optimistic scenario for the future of India's energy economy.

1.2 **Role of RE in India's energy economy**

In December 2016, RE (solar, wind and biomass) accounted for 45.9 GW (around 15%) of electricity capacity in India, of which wind and solar comprised 28 GW and 8.5 GW respectively (Central Electricity Authority, 2016). This amounted to a mere 0.8% of total primary energy supply, pointing toward significant potential for increasing its exploitation, especially in light of its resource abundance and steadily falling costs (IEA Statistics).

India is endowed with a large and untapped potential for RE capacity. Recent estimates show that India's solar PV potential is greater than 11000 GW and wind potential is in excess of 3000 GW. The India Energy Security Scenarios 2047 indicate the possibility of achieving around 551 GW of wind and 807 GW of solar PV by the year 2047. The potential for biomass, waste and small hydro is also significant (NITI Aayog and IEEJ, 2017). These indicate a leap-frogging from the prevailing low levels of around 46 GW in 2016.

The costs of RE (especially solar and wind) have displayed a continuously declining cost trajectory. Although both wind and solar still require subsidies to incentivize investment, the trends for future costs bode well for increasing market penetration. For solar, the recent trends imply that, between 2010 and 2015, the average levelized cost of electricity generated by utility-scale solar in India had fallen by around half, largely reflecting a decline in the investment costs for solar cells. India's Energy Outlook (IEA/ IEO, 2015) predicts that these costs would continue to decline throughout the projection period, falling by over 45% to 2040, by which time the levelized cost of electricity will be like that of wind power and coming close to full convergence with the average cost of power generation in the Indian system.

While the current levelized costs of offshore wind power are significantly lower than solar photovoltaic (PV), these are not expected to depict a sharp decline in the future, falling by only 18% to 2040. This reflects the fact that, as more and more wind resource is tapped, it deems it necessary to install increasingly taller towers with wider turbine blades to maintain efficiency, which entail higher capital costs. Further, these set in diminishing returns to further technological improvement and learning-by-doing, as wind turbine technology gets standardized globally, thus exhausting the potential for further efficiency improvements. Nevertheless, the costs of onshore wind tend to fall from being around 60% higher to being much closer to the average power generation costs for the system as a whole (IEA/ IEO, 2015).

In sum, because of its abundant potential and improving financial viability, RE offers a significant potential to contribute toward the growth and development of India's electricity sector. Bearing this in mind, the Government of India has put out an ambitious plan of achieving 175 GW of RE by 2022. In view of the prevailing thrust on higher RE targets as well as an escalating share of RE in the total energy mix, it is important to understand the policy framework within which RE is being promoted.

1.3 Policy framework for RE in India

India has had a well-diversified portfolio of regulatory policies as well as fiscal incentives and public financing for RE development and deployment. These have included feed-in-tariffs, RE portfolio, tradable RE certificates (RECs), production tax credit, tendering, net metering, and capital subsidies among others. It represents the world's 6th largest RE market (REN 21, 2013). According to the Global Status Report, 2016, India is among the top five countries investing in hydropower, concentrated solar power, wind power, and solar water heating capacity. It is also among the top nations for total capacity or generation of renewable power (excluding hydropower) as at the end of 2015. The RE capacity in the country stood at nearly 46 GW in at the end of 2016 (Central Electricity Authority, 2016). In order to overcome the cost barriers, fiscal incentives are being provided like the

Generation Based Incentive (GBI) scheme which pays USD 0.01/kWh to producers (REN21, 2014).

Most of the states are complementing reverse bidding program with a feed-in-tariff as a ceiling cap for tariff rates for solar PV. For wind projects, feed-in-tariffs are taken up without bidding programs. These have been facilitated with the help of the Jawaharlal Nehru National Solar Mission (JNNSM) laid by the National Action Plan on Climate Change (NAPCC, 2008) and state government policies. In addition to this, prices fell from 35c/ kWh to less than 17c/ kWh due to reverse bidding process making the renewable sources competitive in comparison with fossil fuel-based energy (CEEW and NRDC, 2012). The civil society in India has played a pivotal role in bridging the information gap regarding the cost of various RE technologies (WWF/ WRI, 2013). In the solar PV industry, manufacturing units operate at low or idle capacity because of less competition, the reason being lack of scale, low cost financing and underdeveloped supply chains. With regard to the weak enforcement and on-compliance issues in implementing renewable portfolio standards (RPOs) amongst states, the Ministry of New and Renewable Energy (MNRE) plays an active role to check any misconduct (Parihar, 2012).

JNNSM is the most successful policy framework toward the deployment of RE, but the domestic content regulation in solar manufacturing industry has attracted strong criticism because of its ineffectiveness. Also, the facilitation of RE technologies is limited to a few states, which restricts the scope for their expansion. Policies and targets vary across states and the Central Electricity Regulatory Commission plays a key role in deciding where the projects should be based. Despite the rapid growth in RE deployment, India continues to face challenges because of lack of transparency, accountability and inadequacy of grid infrastructure facilities (WWF and WRI, 2013). Insufficient trained manpower, weak transmission networks and delays in payment by distribution companies (DISCOMS) also pose a challenge to the growth of RE technologies (Government of India, 2006 and MNRE 2012). Improvements on these fronts can increase investor confidence and governance, thereby enhancing scope of RE in the country (Mehra and Pandey, 2017; Pandey and Mehra, 2017).

A brief discussion on the individual RE technologies is now provided.

1.3.1 SOLAR ENERGY

The geographical location of India provides a large potential for solar power. About 3300 to 3700 hours of bright sunshine are available in a year in the northwest and west-central regions of the country. The total solar energy received by the subcontinent is over $60 \times (10)^{13}$ Megawatt hour (Basu et al., 2015). This ensures solar energy to be one of the most promising sources of non-conventional energy.

The 4th Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), 2007, prompted the government to initiate effective measures to spur the growth of RE as a means to mitigate climate change. This resulted in the formation of NAPCC. The primary objective of NAPCC was to promote the development of the economy with special emphasis on climate change. It also aimed at developing energy efficient technologies in order to address climate change issues related to adaptation and mitigation. The National Solar Mission, one of the eight national missions, was launched to increase the share of solar energy in the total energy mix as a step towards promotion of RE use. This was accompanied by a push towards integrating solar with other RE sources like wind, biomass, etc.

The JNNSM, launched in 2010, is also one of the pioneering steps toward a shift of dependence in favor of RE. The MNRE has estimated the potential of 749 GW of solar power while the cumulative achievement as on December 31, 2015 was 4.9 GW. The fastest advancement has taken place in case of utility-scale solar PV projects, with capacity increases from 3 GW in 2014 to 4 GW in 2015. In the case of rooftop solar installations, the performance has been rather ordinary, with a mere 450 MW of installed capacity in 2014. The installed capacity for concentrated solar power (CSP) has been 200 MW. The national target of 100 GW of installed capacity by 2022 is split between 60 gigawatts of utility-scale projects including solar PV and CSP and 40 gigawatts of rooftop solar applications for commercial users and households. With China taking the lead, India could emerge as the second largest solar market globally with a projection of 188 gigawatts of installed capacity by 2040, and its share at 17% in total power capacity. In addition, the average levelized cost of electricity generated by utility scale solar PV has fallen by half since 2010, resulting in a decline in investment costs. It is further expected to decline by 45% by 2040 (IEA/ IEO, 2015).

Despite its stupendous growth, the solar sector is beset with several impediments, such as grid management and problems of intermittency, since solar power generation cannot take place for 24 hours in a day. The difficulty of enforcing purchase obligations, delays in payments and land acquisition issues also loom large.

In order to send a strong signal to the international community about India's concern over climate change and its steadfast initiative to achieve low carbon intensity, the Prime Minister of India launched the program called the International Solar Alliance (ISA) at the United Nations Climate Change Conference held in Paris in 2015. The alliance includes 121 sun-rich countries across the globe whose geographical location falls either fully or partly within the tropics. With headquarters in Gurgaon, Haryana, India, the initiative aims to harness solar energy and ensure cooperative deployment of energy, technology diffusion and investments in joint ventures. The initial budget outlay for ISA is US$ 30 million, with gradual increments in the years to come.

1.3.2 WIND ENERGY

The National Institute of Wind Energy of India estimates its total onshore wind power potential with a hub height of 100 meters at 302 GW. The most promising sights are located in the western and southern parts of India, including states like Andhra Pradesh, Gujarat, Karnataka, Madhya Pradesh, Maharashtra, Rajasthan, Tamil Nadu and Telangana. Wind power generation is projected to rise sharply from 23 GW to 142 GW of installed capacity by 2040.

The MNRE has introduced different schemes and incentives to promote wind energy development in India, such as Accelerated Depreciation (AD), Generation Based Incentive (GBI), National Wind Mission (NWM, 2014) and National Offshore Wind Energy Policy (2015) etc. in this regard.

However, this sector has been facing many challenges in terms of land acquisition issues for onshore wind power, delays in approval process, staggered pace of agreement for power purchase by distribution utilities, etc. Revenue under recovery by the electricity distribution companies (DISCOMS) has resulted in payment delays by 6 to 24 weeks. Such delays curtail 3-4% of internal rate of return (IRR), jeopardizing the viability of the project. Offshore wind farms may avert land acquisition issues but face huge capital costs. The onshore wind power cost is projected to decline by only 18% by 2040. In order to maintain efficiency, taller towers with large turbine blades have to be installed, which are costly. Limited scope for technological improvement and local learning has contributed to the non-competitiveness of wind power projects.

1.3.3 BIOMASS ENERGY

Biomass is a resource that could play a more substantial role in India's energy sector through greater diversification and sustainable energy mix. The energy obtained from biomass is a form of RE and, in principle, utilizing this energy does not add CO_2, a major greenhouse gas, to the atmosphere, in contrast to fossil energy (FE) (Kumar et.al., 2010). Biomass covers different materials, such as firewood collected from farmland, natural woods, food wastes, food processing wastes etc. In India biomass power generation attracts over Rs. 6 billion investment every year, generating more than 5000 million units of electricity and yearly employment of more than 10 million man-days in rural areas (Kumar et.al., 2010).

Approximately 500 biomass power and cogeneration projects, aggregating to a capacity of about 4760 MW, have been installed in India for feeding power to the grid. Further, around 30 biomass power projects, aggregating nearly 350 MW, are under various stages of implementation to facilitate setting up of biomass plants. Central Financial Assistance (CFA) is also extended to developers. Concessional customs duty and excise duty exemption are also made available to the developers on initial set up of biomass projects. Indian Renewable Energy Development Agency (IREDA) also supports through loans for the setting up of biomass power and bagasse cogeneration projects.

1.4 Targets for RE in India

The national targets for RE are set in consonance with the national five-year plans as well as the NAPCC, 2008. The Government of India has an ambitious plan of achieving 175 GW of RE by 2022, of which the break-up proposed across technologies is: 100 GW of solar, 60 GW of wind, 10 GW of biomass and 5 GW of small hydro. According to NITI (National Institution for Transforming India) Aayog, the growth of RE is going to be enormous in the next few years, with proposed incremental installations of 20.2 GW in 2017-18, 21.8 GW in 2018-19, 23.5 GW in 2019-20, 24.7 GW in 2020-21 and 27.5 GW in 2021-22 (NITI Aayog and IEEJ, 2017). Accordingly, if realized, this would contribute around 18.9% of power consumption in India in 2022.

1.5 Motivation for and scope of this research

In view of energy being a crucial input for the growth and development of an economy, both FE and RE have strong backward and forward linkages with key factors characterizing the macroeconomy, demographics and the energy economy of India. In view of the ambitious RE targets that India has set to achieve over the next five years or so, it is important to examine rigorously the role that RE will play in terms of its interaction with key variables that include GDP, population, fiscal deficit, capital borrowing and lending rates (indicative of return on capital investment), energy import dependence, energy access (rural electrification and access to clean fuels), employment etc. The linkages with employment are large and unexploited. It is claimed that the growth of the RE markets across India could help stimulate local economies and enhance job creation (CEEW and NRDC, 2015). In fact, Jain and Patwardhan (2013), who have estimated the employment effects of RE targets, conclude that RE technologies create more jobs per unit of installed capacity and per unit of power generated than FE technologies.

All of the above deem it necessary to carry out a formal analysis that attempts to find answers to the following questions:

- What are the important linkages between macro-economic variables (GDP, population, employment, fiscal deficit, energy imports, energy access, return on capital etc.) and RE deployment in India?
- What would the above relationship(s) imply for RE diffusion in India, under alternative regimes of key macro-economic and demographic variables, both in the medium- and long-run time frames?
- What would be the forecasts of RE generation and RE capacity in the medium- and long-runs?
- What will be the impact of RE diffusion on employment generation in the RE sector?
- What are the implication of RE penetration and associated movement of key macro-economic and financial variables and other factors, for India's energy security, as captured by a composite energy security index?

To answer the above questions, we utilize macro-econometrics and time series methods for our analyses. These include tests of stationarity, Granger causality tests and a cointegration exercise using Auto Regressive Distributed Lag (ARDL) model structure for our estimation. The level of employment generation is linked to the incremental RE capacity in future years, based on normative data. For preparing the energy security index, a set of energy security indicators or dimensions are considered, and a distance-function approach is utilized.

Accordingly, the remaining sections are organized as follows. Section 2 provides a discussion of the specific methods and models that are used for establishing the relationship between RE and key macroeconomic variables, lays out the results and provides a discussion on these, in terms of its key messages (See Appendix A for a review of literature on different methods that have been used by other studies to model the energy-economy in general, and the role of RE versus FE in particular.). Section 3 lays down the assumptions for forecasting the RE penetration in the medium- and long-runs under alternative macroeconomic and demographic scenarios for India, as well as it presents and discusses the results of this forecasting exercise. Section 4 utilizes the estimates of Sections 2 and 3 to forecast the job-creation potential for RE in India, based on normative data. Section 5 discusses the methods used and results of understanding the impact of alternative RE penetration on India's energy security; this is done by preparing a composite index of energy security, for the current and future years, under alternative scenarios. Section 6 summarizes the important takeaways from this research, and concludes.

2. RE growth and its macroeconomic linkages in India

As alluded to earlier, we now lay out the methods and models adopted for our macro-econometric time series estimation that will help us find the long-run equilibrium relationship among RE supply/ generation and other macroeconomic variables, namely, economic growth, unemployment rate, fiscal deficits, net energy imports, population, call rate etc. for India (for detailed definitions, refer to Appendix B). This would help ascertain the long-run co-movement of variables in time.

For this, unit-root tests were performed to find out whether the time-series variables are stationary (non-stationary), that is, whether a shift in time doesn't (does) cause a change in the shape of the distribution. Thus, stationarity amounts to the basic properties of the distribution, like the mean, variance and covariance, being constant over time. Next, Granger causality tests have also been attempted, which is a statistical concept of causality that is based on prediction. These Granger causality tests, done for any pair of variables (considered by us), show which way the causality between them works. These are useful in discerning the underlying relationships that help setting up the macro-econometric model. Finally, an ARDL model is estimated, which is a time-series econometric methodology used for establishing the relationship between RE, on one hand, and the macro variables, on the other, over time. This estimated relationship helps predict RE generation and associated RE capacity in the future.

2.1 Methods and models

2.1.1 TESTS OF STATIONARITY

The empirical research is based on time series data and assumes that the underlying time series variable is stationary. A stationary time series process has the property that its mean, variance and auto-correlation structures do not change over time. While stationarity can be defined in precise mathematical terms, for our purpose suffice is to say that it means a flat looking series, without trend, constant variance over time, a constant auto-correlation structure over time, and with no periodic fluctuations. Such a time series will return to its mean, and the fluctuations around its mean, captured by the variance, will have a broadly constant amplitude (Gujarati, 2003). Regression models that use time series data are often used for forecasting, as is the case in our analysis. In general, such forecasting would require that the underlying time series variable is stationary. If the series is non-stationary, one can analyze its behavior only over the time period for which the data are available, and it would not be possible to generalize it to other time periods. Thus, for forecasting purposes, non-stationary time series will not be useful.

The tests of stationarity are usually called the unit-root test, which show whether the series under consideration is stationary or non-stationary. It is appropriate for most of the time-series variables to be tested for whether these have a unit root or not. If a variable contains a unit root at levels, then it is said that the variable is non-stationary at levels. Even to apply the Granger causality test we need all the variables to be stationary. The pioneering work for unit root test in time-series was done by Dickey and Fuller (Fuller, 1976; Dickey and Fuller, 1979). For our analysis, the unit-root test used is the modified Dickey–Fuller test (known as the DF-GLS test) proposed by Elliott, Rothenberg, and Stock (1996). More rigorous details on this test can be found in Appendix C.

2.1.2 GRANGER CAUSALITY TESTS

The Granger causality test is a statistical test that is used for determining whether one time-series is useful in forecasting another. Typically, regressions reflect "mere" correlations, but Clive Granger argued that causality could be tested for by measuring the ability to predict the future values of a time-series by using prior values of another time series. Specifically, according to Granger causality, if a variable Y "Granger-causes" another variable X, then the past values of Y should contain information that helps predict X above and beyond the information contained in the past values of X alone. Mathematical details on Granger causality tests can be found in Appendix D.

2.1.3 ARDL MODEL

The ARDL model is being commonly used to model the relationship or co-movement between (economic) variables in a single-equation time-series setup. ARDL models are standard least squares regressions that include lags of both the dependent variable and explanatory variables as regressors (Greene, 2008). ARDL model was introduced by Pesaran et. al. (2001) in order to incorporate stationary, or integrated of order zero, i.e., I(0), and non-stationary, integrated of order 1, i.e., I(1), time series variables in the same estimation so that, if the variables are stationary (i.e. I(0)) then OLS is appropriate, and if all are non-stationary (i.e. I(1)) then it is advisable to use the vector error correction (VECM) (Johansen, 1988, 1991) as it is a much simpler model. Again, a more detailed exposition of the ARDL method is provided in Appendix E.

In what follows, the results of the unit-root tests, Granger causality and ARDL model estimation are presented and discussed.

2.2 Data set

The dataset used in this research is extracted on annual basis, and the time period of the dataset ranges from 1990 and 2016, that is 27 years.

The variables considered for India at the macro level are: gross domestic product at constant prices (GDP_CONS_01), aggregate population (POP), unemployment rate (UNEMP), gross fiscal deficit (FIS_DEF), interest rates (CALL_RATE), renewable energy generation (solar, wind and biogas) (RE_02), total primary energy supply (TPES_01), net energy imports (NET_EN_IMP), annual energy outlay (EN_OUT), population with access to electricity (POP_ACCESS_PERCENT), and RE versus FE tariff (RE_TO_FE_TARIFF).

The data on GDP_CONS_01, POP, POP_ACCESS_PERCENT and UNEMP have been obtained from the World Development Indicators (various issues), World Bank database. The data series on CALL_RATE and FIS_DEF are extracted from the Reserve Bank of India database. Next, the dataset on RE_02, TPES_01 and NET_EN_IMP have been obtained from the country-level energy balances of the International Energy Agency from their online database. The time series on EN_OUT is from the Economic Survey (various issues) brought out annually by the Ministry of Finance, Government of India. Finally, the series on the ratio RE_TO_FE_TARIFFS is calculated by the authors from the Central Electricity Regulatory Commission's (CERC's annual reports, various issues).

The units of measurement of these variables as well as the detailed data source are provided in Table 1 below:

Table 1: Variables names, units of measurement and data sources

Variable	Code	Unit	Source
Gross domestic product	GDP_CONS_01	Billion INR at constant prices (2011-12)	World Bank
Population	POP	Billions	World Bank
Unemployment rate	UNEMP	Percentage	World Bank
Gross fiscal deficit	FIS_DEF	Billion INR at current prices	Handbook of Statistics on the Indian Economy, Reserve Bank of India
Interest rate/ call rate	CALL_RATE	Percentage	Database on Indian Economy, Reserve Bank of India
Renewable energy (Solar, wind, biogas)	RE_02	Million tons of oil equivalent (MTOE)	Country Statistics, International Energy Agency
Total primary energy supply	TPES_01	MTOE	Statistics, International Energy Agency
Net energy imports	NET_EN_IMP	MTOE	Statistics, International Energy Agency
Energy outlay	EN_OUT	Billion INR at current prices	Handbook of Statistics on the Indian Economy, Reserve Bank of India
Percentage of population with access to electricity	POP_ACCESS_PERCENT	Percentage	World Bank
Relative tariffs (RE to FE)	RE_TO_FE_TARIFF	Unit free	Annual Reports, Central Electricity Regulatory Commission

For a few years for select variables, the data for the relevant variables were found missing. These missing data points have been filled in by using the method of interpolation.

2.3 Results

2.3.1 UNIT ROOT TEST RESULTS

The specific test used in this study, to check for the presence of unit-root in the variables, relies on the DF-GLS method. This performs the modified Dickey–Fuller t-test (known as the DF-GLS test) proposed by Elliott, Rothenberg, and Stock (1996). Basically, the test is an extended version of the Augmented Dickey–Fuller test, where the time-series is transformed via generalized least squares (GLS) regression before performing the test. Elliott, Rothenberg, and Stock (1996), and later some other studies, have shown that this test has a significantly greater power over the previous versions of the Augmented Dickey-Fuller test.

The main results of the DF-GLS test for all the variables considered for our analysis are tabulated below (Table 2).

Table 2: Results of DF-GLS unit-root test

Variable Name	Order of Integration
GDP_CONS_01	I(1)
POP	I(0)
UNEMP	I(0)
FIS_DEF	I(1)
CALL_RATE	I(0)
RE_02	I(1)
TPES_01	I(1)
NET_EN_IMP	I(1)
EN_OUT	I(0)
POP_ACCESS_PERCENT	I(0)
RE_TO_FE_TARIFF	I(1)

Source: Authors' calculations

The results in Table 2 show that the variables, GDP_CONS_01, FIS_DEF, RE_02, TPES_01, NET_EN_IMP and ratio of RE_to_FE_TARIFF are non stationary, i.e., integrated of order one or I(1). The remianing variables, such as POP, CALL_RATE, UNEMP, EN_OUT and POP_ACCESS_PERCENT are found to be stationary, namely, integrated of order zero or I(0).

More detailed results of these tests can be found in Appendix C.

2.3.2 GRANGER CAUSALITY TEST RESULTS

The following two tables (Tables 3 and 4) shows the results of the Granger causality test for different variables at different lags.

Table 3: Results of the Granger causality tests

Granger causality from X → Y	Lags	Level of significance corresponding to the lags
D_RE_02 →CALL_RATE	5	10%
D_FIS_DEF→ D_RE_02	2, 3	5%, 5%
D_RE_02→ D_FIS_DEF	5	5%
D_GDP_CONS_01 → D_RE_02	2, 3, 4	5%, 5%, 5%
D_RE_02→ D_NET_EN _IMP	2, 3, 4	5%, 5%, 5%
D_RE_TO_FE_TARIFF → D_RE_02	5, 6, 7	10%, 5%, 5%
D_RE_02→ D_RE_TO_FE_TARIFF	7	5%
POP→D_RE_02	2, 3	5%, 10%
D_RE_02→ POP	3, 4	10%, 5%

POP_ACCESS_PERCENT→ D_RE_02	2, 3, 4	5%, 5%, 5%
D_RE_02 →POP_ACCESS_PERCENT	2, 4	5%, 5%
D_RE_02→UNEMP	2, 4, 5, 6	10%, 10%, 10%, 5%

Source: Authors' calculations

Table 4: Direction of relation between key variables

Direction of relation	Cases
Unidirectional from RE	RE→CALL_RATE
	RE→FISCAL_DEFICIT
	RE→NET_ENERGY_IMPORTS
	RE→UNEMPLOYMENT_RATE
Unidirectional toward RE	RE←GDP
Bi-directional	RE↔FISCAL_DEFICIT
	RE↔RE_TO_FE_TARIFF
	RE↔POPULATION
	RE↔POPULATION_ACCESS_PERCENTAGE

As can be seen, RE_02 Granger causes CALL_RATE, while FIS_DEF and RE_02 display a two-way causality. Further, GDP_CONS_01 Granger causes RE_02, RE_02 Granger causes NET_EN_IMP, and there is a two-way causality between RE_02 and RE_TO_FE_TARIFF, RE_02 and POP, and RE_02 and POP_ACCESS_PERCENT. Finally, RE_02 Granger causes UNEMP. These causalities help explain later the relationships as derived from the cointegration ARDL equation.

2.3.3 ARDL MODEL ESTIMATES AND INTERPRETATION

The Johansen cointegration test result showed that the variables are co-integrated. The VECM estimation results were not found to be satisfactory as the error correction term was not convergent. Moreover, the VECM methodology was unable to incorporate a combination of I(0) and I(1) variables. So, we resorted to ARDL model estimation, as the unit root tests revealed that some of the variables mentioned above were I(0), while some other important ones were I(1). Several combinations of variables were checked for that could potentially determine the penetration of RE in India. Different lag specifications were used to estimate the ARDL model.

We found the following stable long-run equilibrium co-integrating ARDL relationship among variables:

$$\mathbf{RE} = 9.2186 + 0.0017*\mathbf{CALL\_RATE} - 0.00004*\mathbf{FIS\_DEF} + 0.00013*\mathbf{GDP} - 0.0017*\mathbf{NET\_EN\_IMP} - 11.6036*\mathbf{POPULATION} - 0.005474*\mathbf{POP\_ACCESS\_PERCENT} + 0.05937*\mathbf{RE\_TO\_FE\ TARIFF} - 0.1475*\mathbf{UNEMP}. \qquad (1)$$

Further, the coefficient associated with the last period error correction term [ECM(-1)] was found to be negative, significant and in between -1 and 0. The coefficient of the last period error correction term, i.e., 0.46, indicates that any short-run deviation in the last period was corrected for in the next period by almost 46%, implying convergence over time.

It can be seen from the equilibrium cointegrating long-run relationship in equation (1) that the long-run GDP_CONS_01, CALL_RATE and RE_TO_FE_TARIFF are positively associated with the penetration of RE(RE_02) while variables such as FIS_DEF, NET_EN_IMP, POP, POP_ACCESS_PERCENT and UNEMP have a negative relationship with RE, (RE_02) penetration in India.

It must be noted that equation (1) is a long run cointegrating relationship between the macroeconomic variables of interest. In other words, it is a linear combination of a set of variables (both I(0) and I(1)) which cannot move independently of each other. In vector algebra, this is termed as linear dependence, where the coefficients are scalars. Consequently, it is incorrect to presume that these coefficients are the marginal effects.

Intuitively, the interpretation of the ARDL method estimates is that the coefficients refer to a specific linear combination of different variables' that capture their co-movement over time. It estimates the co-integrating vector. Thus, while the signs provide an indication of this movement of a variable being co-cyclical or counter-cyclical to other variables, it would not be a valid exercise to capture changes in one of them alone, in terms of the impact on another variable, while holding all others constant, since time series estimates the manner in which they all co-move.

The results of the bound test for our case are reported in the following table (Table 5).

Table 5: The ARDL bound test results

Calculated F-statistics	Df	10% Critical value		5% Critical value		1% Critical value	
		Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
5.47	8	1.85	2.85	2.11	3.15	2.62	3.77

Source: Authors' calculations

As can be found from the statistics in the above table (Table 5), the calculated F-statistics is greater than both the lower bound critical values and as well as the upper bound critical values at all the levels of significance. Thus, the null hypothesis of the non-existence of no long-run relation among the variables is rejected (see the explanation for this test in Appendix D).

The results in equation (1) can be interpreted as follows.

RE generation (RE_02) is positively related to CALL_RATE, as the coefficient of CALL_RATE in the right-hand side of equation (1) is 0.0017. In general, a higher CALL_RATE constitutes either the cost of capital (that may dampen investment in RE) or a return on capital investment (that encourages investment in RE equipment). At the macro-level, the latter effect outweighs the former, implying that RE_02 and CALL_RATE move pro-cyclically.

Notably, in equation (1) the coefficient attached with the variables FIS_DEF is negative, at -0.00004, indicating that RE generation (or RE_02) moves negatively with FIS_DEF. Note that, ARDL captures the co-movement of the macro variables. Here, in the aggregate, a higher FIS_DEF is largely indicative of financial support (including subsidies) to FE generation. Furthermore, RE prices are now determined through reverse auctions by private companies. This has allayed the dependence on feed-in-tariffs. Consequently, a higher level of RE penetration will now be associated with lower fiscal deficit on account of a lower share of FE generation. The direction of this relationship might change as more data become available on FE penetration.

RE generation (that is, RE_02) is also positively related to GDP_CONS_01. The coefficient estimated for GDP_CONS_01 in equation (1) is 0.00013, implying that higher incomes induce a higher willingness to pay for RE or a higher demand for RE, hence the positive relationship. This could also be due to the fact that RE is a normal good, implying cleaner energy is demanded more at higher incomes, entailing a pro-cyclical relationship between these two variables.

RE_02 is found to have a negative relationship with NET_EN_IMP, which is expected. This is evident from the coefficient attached with NET-EN_IMP being -0.0017. On the average, a higher RE generation is associated with lower energy imports, which in India, have a preponderance of FE. Thus, RE substitutes for FE in the aggregate, implying a counter-cyclical movement between these two variables.

Interestingly, with aggregate POP, and POP_ACCESS_PERCENT, RE generation (RE_02) has a negative correlation, or that, it moves counter-cyclically. The respective coefficients associated with POP and POP_ACCESS_PERCENT are -11.6036 and -0.005474. A higher population level or a higher access of population to electricity places a heavier demand on the economy in terms of demand for energy. Given the limited time series dataset (for 27 years only) and India's excessive dependence on FE, so far, the estimation shows that both -- higher population or population access to electricity -- tend to dampen RE penetration – or that these move in opposite directions over time. The direction of this link may undergo a change as more RE diffusion happens.

A positive coefficient of 0.05937 with the variable RE_TO_FE TARIFF implies that RE_02 and relative RE to FE tariffs move in a positive manner. This is due to the fact that a higher RE_TO_FE TARIFF implies a more remunerative tariff for RE, entailing higher diffusion for it.

The coefficient of UNEMP in the right-hand side of equation (1) is -0.1475 RE generation (RE_02) is also found to move negatively, or counter-cyclically, with aggregate UNEMP in the Indian economy. A higher RE diffusion is typically associated with lower unemployment rates, at the economy-wide level.

In sum, the study finds that RE diffusion in India is positively associated with GDP_CONS, CALL_RATE and RE_TO_FE_TARIFF and negatively associated with FIS_DEF, NET_EN_IMP, POP, POP_ACCESS_PERCENT and UNEMP. These relationships point toward significant policy implications, such as a higher economic growth rate, a higher return on investment, and more remunerative RE tariff would spur RE growth. Alternatively, a higher fiscal deficit, and energy imports will dampen RE diffusion and vice versa. Similarly, in terms of further policy implications for India, a case can be made for the fact that a higher level of population, or a higher share of population in terms of energy access will imply greater reliance on FE rather than RE.

Utilizing the ARDL estimated equation in (1), three different scenarios, namely, business as usual (BAU), pessimistic and optimistic are postulated for forecasting different levels of RE penetration in India's energy economy. The forecasts of RE generation and associated RE capacity are made for the years 2018-2042, for each of the three scenarios.

In what ensues, a discussion on the assumptions, methods and models used for forecasting is presented.

3. Forecasting of RE generation and associated capacities in India under alternative scenarios

Based on the estimated long-run stable co-integrating relationship among the variables using the ARDL model, that is defined in equation (1), three different scenarios, namely, BAU, pessimistic and optimistic are formulated.

The three scenarios constructed are derived from alternative official trends or policy-targets having implications on key macro variables projected for the Indian economy. As will be explained, the authors have relied on a detailed reading of the government documents and other policy papers to judiciously construct these scenarios. The ARDL equations estimated can be used creating alternative configuration of assumptions to construct many more scenarios and carry out the sensitivity analysis on RE and jobs, where the latter are discussed in the next section).

The BAU depicts the business-as-usual scenario for RE penetration, implying a continuation of the past trends and policies, with no significant structural breaks. The optimistic scenario describes a situation where the movement of the driving variables is such that these spur the growth of RE more positively than in the BAU. Alternatively, the pessimistic scenario describes a situation where all the key driving macro -economic variables move in a manner in the future years such that they adversely affect RE diffusion. Thus, both optimistic and pessimistic scenarios imply important policy and structural changes, which are not modeled explicitly, but rather driven through changes in these macro variables.

In what follows immediately, the specification of the path of the key variables that drive these three different scenarios is presented and discussed.

3.1 Assumptions underlying alternative RE forecasts

3.1.1 CALL RATE

The call rate (CALL_RATE) is assumed to be the same across all the three scenarios, as the decision of the central bank is made independently, based on the macro fundamentals and monetary policy of the country, and has little link with any policy toward RE penetration alone. The average weighted monthly call money rate of the Reserve Bank of India (RBI) for most of the past months in 2017 has been found to be around 6%. Thus, starting with a 6% rate in 2017, we consider it to remain unchanged until the end of the year 2019. Further, over time, the call money rate is assumed to taper-off slowly and become constant at around 5% into the future, until 2042. The specification assumptions for these years are mentioned in the following table (Table 6).

Table 6: Forecasted values of call rate for the BAU, optimistic and pessimistic scenarios (per cent)

Year	Call Rate
2017-19	6
2020-24	5.8
2025-29	5.6
2030-34	5.5
2035-42	5

3.1.2 GROSS FISCAL DEFICIT (AS A PERCENTAGE OF GDP)

For gross fiscal deficit percentage (FIS_DEF), the baseline (BAU) scenario has been defined based on the figures by the NITI Aayog report titled, "Three Year Action Agenda, 2017-18 to 2019-20" (NITI Aayog, 2017). Under the optimistic scenario, FIS_DEF is assumed to fall at a slower rate than in the case of the BAU, due to a rise in the public expenditure for developmental activities. In contrast, the pessimistic scenario is characterized by a fall in FIS_DEF at rate higher than in case of the optimistic scenario as well as the BAU. For specific values assumed, see Table 7 below.

Table 7: Forecasted values of gross fiscal deficit under different scenarios (per cent)

Year	BAU	Optimistic	Pessimistic
2017-19	3.45	3.45	3.45
2020-24	3.30	3.45	3.20
2025-29	3.20	3.30	3.10
2030-34	3.00	3.20	3.00
2035-42	3.00	3.00	2.90

3.1.3 GDP GROWTH RATE

Business as Usual

The annual GDP growth rate (growth of GDP_CONS_01) for the year 2017 has been fixed at 7.1%, following the forecasts by the World Bank and RBI. Under the BAU scenario, the economy is expected to grow at the same rate until the years 2020-2024, where the growth rate increases to 7.5% per annum. For the next ten years, the growth rate rises to 8% annually. For 2035-2039, the growth rate is assumed to be 8.2%. Further, from 2040 onwards, it is assumed to be at 8.5% (see Table 8).

Optimistic

Under this scenario, the annual growth rate (of GDP_CONS_01) accelerates from 7.1% in 2019 to 9% in 2040-42. The transition takes place from 2020, where GDP grows at the rate of 8% per annum up until 2024, and then by 8.2% till 2029. From 2030 onward, the annual growth rate is assumed to be 8.5% followed by 8.8% for 2035-2039. Again, refer to Table 8 for this case.

Pessimistic

The pessimistic scenario is characterized by a deceleration in the annual GDP growth rate (of GDP_CONS_01) from 7.1% in 2017-2019 to 5% in 2035-2042. The time path is shown below (Table 8).

Table 8: Forecasted values of annual GDP growth rate under different scenarios (per cent)

Year	BAU	Optimistic	Pessimistic
2017	7.1	7.1	7.1
2018-19	7.1	7.5	6.75
2020-24	7.5	8	6.5
2025-34	8	8.2	6
2035-39	8.2	8.5	5.5
2040-42	8.5	8.8	5
		9	5

3.1.4 NET ENERGY IMPORTS (AS A PERCENTAGE OF TOTAL PRIMARY ENERGY SUPPLY)

The BAU scenario for net energy imports share (share of NET_EN_IMP in TPES_01) is based on the forecasts by the India Energy Outlook, World Energy Outlook Special Report, 2015. NITI Aayog's report on "Draft National Energy Policy (2017) forecasts NET_EN_IMP's share in TPES_01 to be around 36-55% (including imports of non-commercial energy) and the "Report on Energy Efficiency and Energy Mix in the Indian Energy System (2030), Using India Energy Security Scenarios, 2047" (2015) also assumes it to be around 45-59.3% under the optimistic scenario. Since we have excluded non-commercial energy from our analysis, the figures for the share of NET_EN_IMP in TPES_01 are assumed to be slightly lower than the afore-mentioned values. For the pessimistic scenario, we have made a 2% addition to the BAU figures. For details, refer to Table 9 below.

Table 9: Forecasted values of share of NET_EN_IMP in TPES under different scenarios (in fraction)

Year	BAU	Optimistic	Pessimistic
2017-19	0.471	0.471	0.471
2020-24	0.450	0.430	0.470
2025-29	0.420	0.400	0.440
2030-34	0.419	0.399	0.439
2035-39	0.415	0.395	0.435
2040-42	0.412	0.392	0.432

3.1.5 POPULATION

The level of total population (that is, POP) for India in the year 2016 was 1.32 billion. The forecasted value of the aggregate population in the year 2017 is taken as 1.33 billion, and considered that it would hover around the same level up till 2019. From the year 2020 onward, population (POP) increases assumed over every five years are shown in Table 10 below. Thus, the average population level for 2020-24 is considered as 1.353 billion, and similarly for the later years, on a five-yearly basis. Furthermore, the level of population is assumed to be same across all the three scenarios.

Table 10: Forecasted levels of population for the BAU, optimistic and pessimistic scenarios (billions)

Year	Population
2017-19	1.33
2020-24	1.353
2025-29	1.37
2030-34	1.39

2035-39	1.4
2040-42	1.45

3.1.6 SHARE OF POPULATION WITH ACCESS TO ELECTRICITY

In the Pradhan Mantri Sahaj Bijli Har Ghar Yojana ('Saubhagya'), it was announced that by the end of 2018 every family, both in rural and urban India, will be fully electrified. But, the analysis of the data suggests that, in 2016, only 82% of the population had access to electricity (POP_ACCESS_PERCENT). Thus, it is rather optimistic to have full electrification by the end of the year 2018. We have, thus, moderated this level by assuming a slower (though steady) rise in the fraction of the population with access to electricity (POP_ACCESS_PERCENT) such that the country gets fully electrified only around the year 2025. The forecasts of population share with access to electricity are the same across the three scenarios (Table 11).

Table 11: Forecasted values of population with access to electricity for BAU, optimistic and pessimistic scenarios (per cent)

Year	Population with access to electricity
2017	84
2018	84.005
2019	84.007
2020	85
2021	85.009
2022	85.011
2023	85.013
2024	85.015
2025-42	100

3.1.7 RE VERSUS FE TARIFFS

The report of the Expert Group on 175 GW RE by 2022 (2015) by NITI Aayog forecasts that the price of RE to conventional coal power price would be equal in 2031-32. Beyond this time point, RE prices would be comparatively lower than coal-fired power prices. Since, this target is quite ambitious, we have assumed more realistic numbers under each of our three scenarios. We expect that the ratio of these prices (RE_TO_FE_TARIFF) would reach 1:1 at the earliest in the pessimistic scenario, followed by the BAU scenario and the optimistic scenario. Our assumptions are quite plausible as we consider these prices to be supply side tariffs. Since relative prices are subject to change based on the regulatory policy, which also happens with some lag, the numbers that were not available for a few intermittent years have been obtained through interpolation. For the specific values, see Table 12 below.

Table 12: Forecasted values of RE versus FE tariff under different scenarios (ratio)

Year	BAU	Optimistic	Pessimistic
2017	1.3428122	1.3428122	1.3428122
2018	1.308531	1.3299568	1.2513956
2019	1.2742498	1.3063884	1.1885467
2020	1.2399685	1.2828201	1.1256978

2021	1.2056873	1.2592517	1.0628489
2022	1.1714061	1.2356834	1
2023	1.1371249	1.2121151	1
2024	1.1028437	1.1885467	1
2025	1.0685624	1.1649784	1
2026	1.0342812	1.14141	1
2027	1	1.1178417	1
2028	1	1.0942734	1
2029	1	1.070705	1
2030	1	1.0471367	1
2031	1	1.0235683	1
2032-42	1	1	1

3.1.8 UNEMPLOYMENT RATE

Business as usual

In the BAU case, the forecasted values of unemployment rate (UNEMP) for 2017 (4.8%) and 2020 (4.6%) are defined by accessing the projected data of unemployment rate from Trading Economics (https://tradingeconomics.com/india/unemployment-rate/forecast, accessed on 13th July 2017). The unemployment rate (UNEMP) in BAU case between 2017 and 2019 is considered to remain at 4.8%. Then onwards, it is assumed that unemployment rate changes only in every five years. Thus, from 2020 to 2024, the unemployment rate (UNEMP) is assumed to remain constant at 4.6%. The forecasts for the unemployment rate for the later years are done for every five-yearly spaced data (such as 2025, 2030, 2035, and 2040) as well and finally, for the year 2042, are also derived similarly. The forecasted values for the years between 2020-2040 (at five-yearly intervals) are taken based on the fact that, over time as the economy progresses, the unemployment rate (UNEMP) will decrease, and starting from 4.6% in 2020, it will become constant at around 4% in 2040-42.

Optimistic

In the optimistic scenario, the forecasted value of UNEMP in the year 2017 is also taken as 4.8%, and it is assumed here as well that for the years 2018 and 2019, the unemployment rate will remain unchanged. But, for the later years (after 2019), it is considered that UNEMP will decrease, and will fall at a faster rate as compared to the BAU scenario. Like in BAU, in the optimistic scenario as well, it is assumed that UNEMP will change in every five years up until 2034, and after 2034, the unemployment rate will stagnate at 3% for the later years.

Pessimistic

The forecast for UNEMP for the pessimistic scenario also starts at 4.8% in the year 2017 and is kept constant till 2019 for our estimations. Later, from the year 2020 to 2024, it is considered that UNEMP will decrease a bit. For the other years starting from 2025 (considering the same assumption that only every five-yearly the unemployment rate would change) and onwards, it is assumed that unemployment rate increases in the pessimistic scenario.

The forecasted values for the UNEMP in the three cases are listed in Table 13.

Table 13: Forecasted values of unemployment rate under different scenarios (per cent)

Year	BAU	Optimistic	Pessimistic

2017-19	4.8	4.8	4.8
2020-24	4.6	4.3	4.7
2025-29	4.5	4	5
2030-34	4.2	3.5	5.5
2035-39	4.1	3	5.8
2040-42	4	3	6

3.2 RE energy and capacity forecasts under alternative scenarios

RE_02 forecasts are done using the estimated cointegration ARDL equation (1) and assuming the future changes in the variables in the right-hand side of this equation as discussed in the foregoing section. The following results are derived (also see Table 14).

As can be seen in Table 14, the growth of RE_02 will be the highest under the optimistic (OPT) scenario reaching a value of over 16.13 MTOE in 2022, 45.08 MTOE in 2032 and 115.83 MTOE in 2042. The corresponding capacity levels for RE_02, by assuming plant capacity utilization of 25%, are found to be 86 GW in 2022, 239 GW in 2032 and a whopping 615 GW in 2042. The estimate for the year 2040 is 510 GW, which is closer to the estimates by the NITI Aayog. The share of energy supplied by RE_02 to TPES_01 is found to increase from the prevailing less than 1% to 1.45% in 2022, 2.86% in 2032 and 5.74% in 2042.

In comparison, the growth under the BAU is closer in the initial years, but the gap widens as a longer period of time elapses. It is estimated at a slightly lower 15.56 MTOE in 2022, 42.15 MTOE in 2032 and 103.16 MTOE in 2042. This amounts to a capacity requirement of 83 GW, 224 GW and 548 GW in the respective years, based on the same plant utilization factor values. Moreover, this amounts to a share of RE_02 to TPES_01 (in MTOE) of 1.42% in 2022, 2.75% in 2032 and 5.15% in 2042.

Table 14: RE_02 (Solar, wind and biogas) energy and capacity forecasts under alternative scenarios

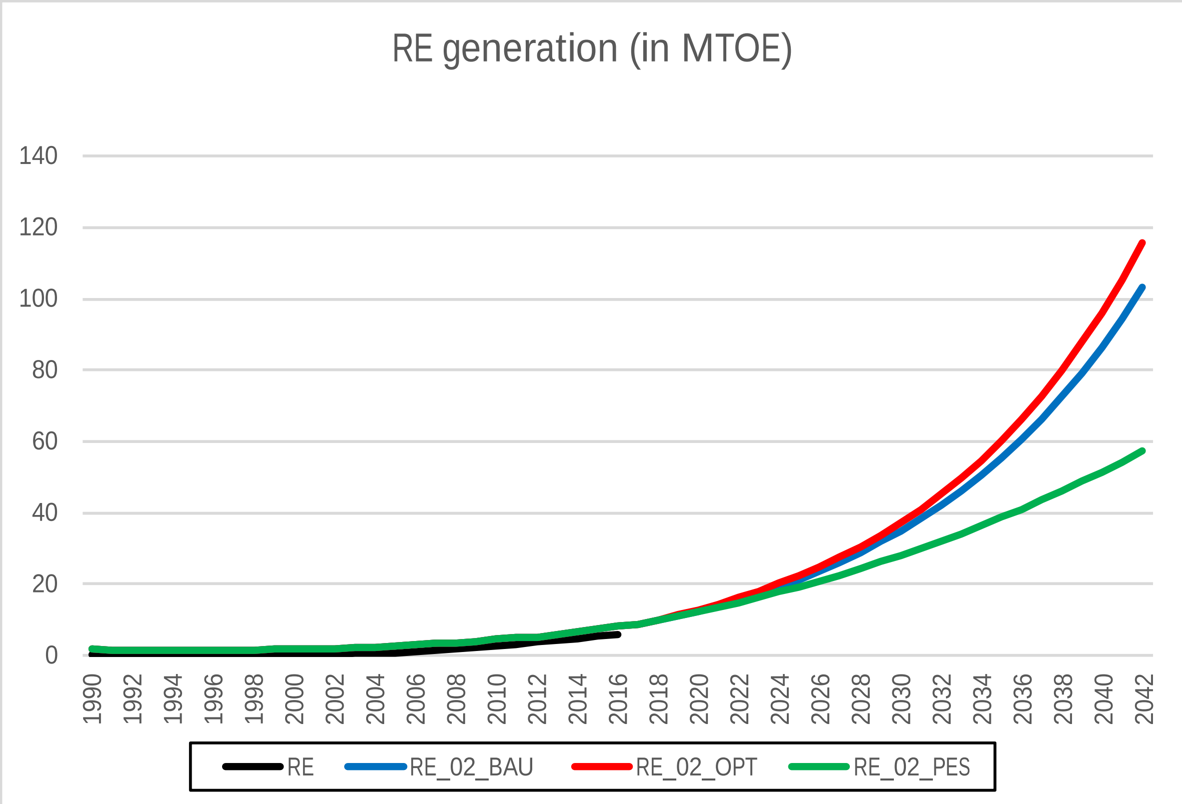
	BAU		**Optimistic**		**Pessimistic**	
Year	RE_02 forecast BAU (in MTOE)	RE_02 capacity OPT (in GW)	RE_02 forecast OPT (in MTOE)	RE_02 capacity BAU (in GW)	RE_02 forecast PES (in MTOE)	RE_02 capacity PES (in GW)
2017	**8.78**	**47**	**8.78**	**47**	**8.78**	**47**
2018	9.94	53	10.00	53	9.89	53
2019	11.18	59	11.32	60	11.07	59
2020	12.39	66	12.71	68	12.04	64
2021	13.92	74	14.36	76	13.33	71
2022	**15.56**	**83**	**16.13**	**86**	**14.71**	**78**
2023	17.32	92	18.06	96	16.18	86
2024	19.22	102	20.14	107	17.75	94
2025	21.21	113	22.29	118	19.04	101
2026	23.56	125	24.78	132	20.68	110
2027	**26.11**	**139**	**27.49**	**146**	**22.41**	**119**
2028	28.87	153	**30.41**	**162**	24.25	129
2029	**31.85**	**169**	**33.59**	**178**	26.21	139
2030	**34.91**	**185**	37.01	197	27.81	148
2031	38.39	204	40.88	217	29.81	158
2032	**42.15**	**224**	**45.08**	**239**	**31.93**	**170**
2033	46.22	245	49.64	264	**34.17**	**181**
2034	50.62	269	54.59	290	36.53	194
2035	55.40	294	60.17	320	38.65	205
2036	60.67	322	66.24	352	41.03	218
2037	**66.37**	**352**	**72.84**	**387**	**43.53**	**231**
2038	72.55	385	80.03	425	46.15	245
2039	79.23	421	87.85	467	48.90	260
2040	86.18	458	95.99	510	51.20	272
2041	94.32	501	105.48	560	54.24	288
2042	**103.16**	**548**	**115.83**	**615**	**57.44**	**305**

Source: Authors' calculations

Finally, under the pessimistic (PES) outlook, the growth of RE_02 is much slower, both in terms of energy supplied and capacity installed, as compared to BAU and OPT. It reaches an energy generation level of 14.71 MTOE in 2022, 31.93 MTOE in 2032 and merely 57.44 in 2042. The associated capacity installed, assuming the same levels of plant capacity utilization values, will be 78 GW, 170 GW and 305 GW in 2022, 2032 and 2042. Accordingly, it is estimated, that the share of RE_02 to TPES_01 will be 1.38% in 2022, 2.12% in 2032 and 2.9% in 2042.

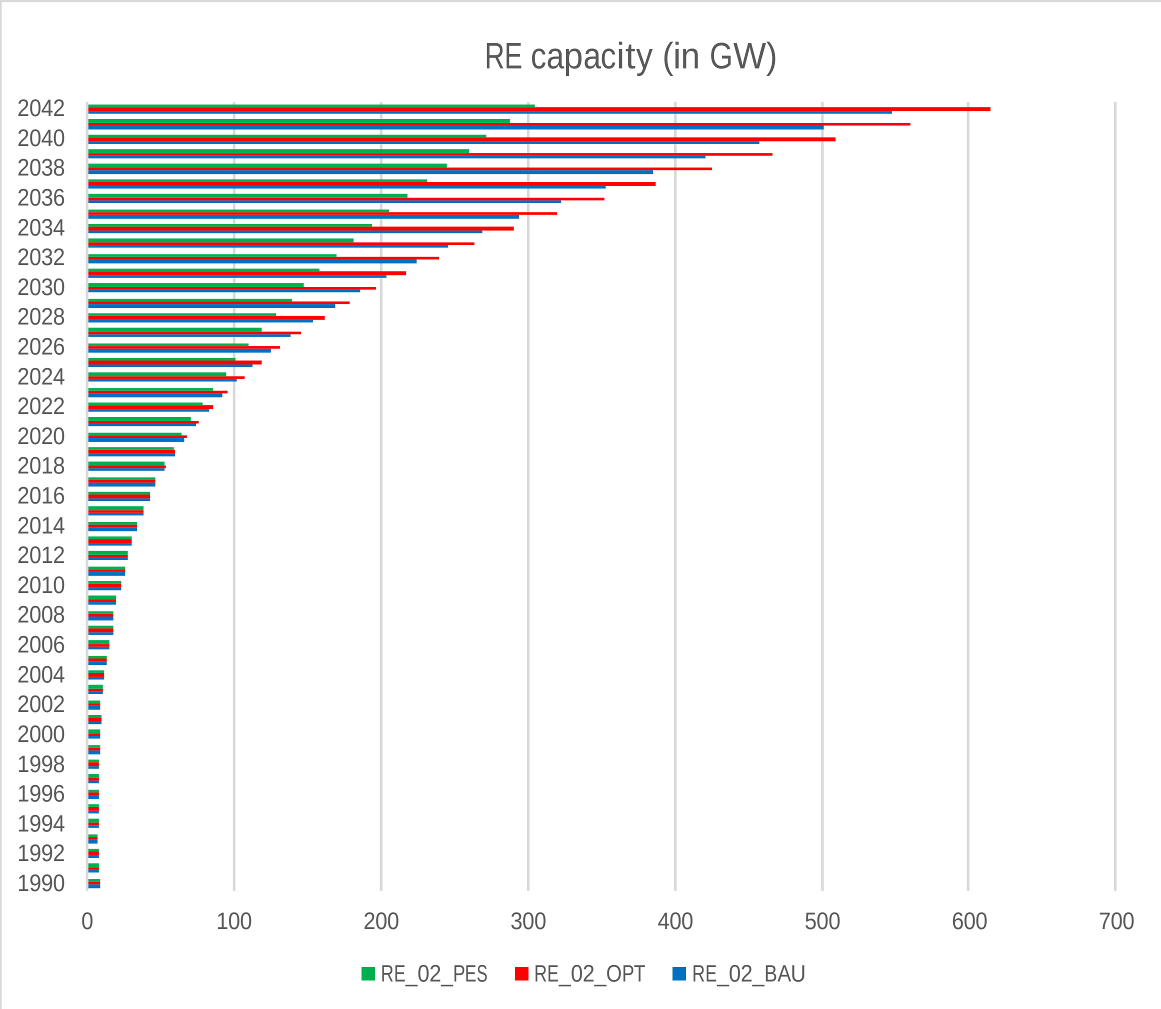
The following three graphs capture these trends over time (see Figures 1-3).

Figure 1: RE generation forecasts under the three scenarios



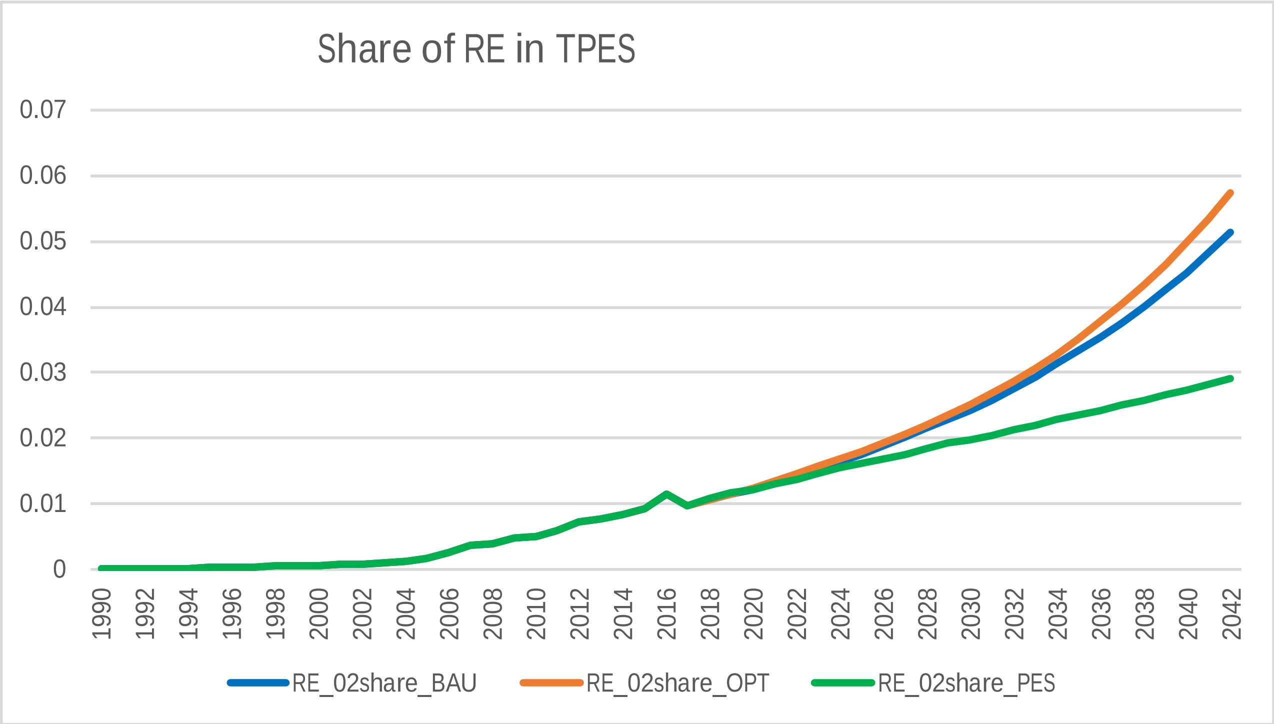
Source: Authors' calculations

Figure 2: RE capacity forecasts under the three scenarios



Source: Authors' calculations

Figure 3: Share of RE in total primary energy supply under the three cases



Source: Authors' calculations

Notably, in comparison with the official targets of RE capacity of 175 GW by 2022 projected by the government, which are discussed in Section 1.4, our estimations show that these are likely to be achieved later in time. This is in consonance with the recent apprehensions expressed in this regard, given the available policy framework moving away from feed-in-tariffs to auctions-based purchases, lack of grid infrastructure and evacuation constraints (Live Mint 2017). Specifically, for instance, we get that the specific government targets are likely to be achieved during 2029-30 under the BAU, a bit earlier, in 2027-28 under the OPT case, and a lot later, in 2032-33 in the PES scenario. Thus, the official forecasts are a bit too ambitious, and plausibly, likely to be achieved later in time, with a delay of between 5 to 10 years, depending on how the macro-economic scenarios, policy execution and technical (grid-related) constraints unfold over time.

4. Future RE capacity and job creation potential

As India strives to enhance the share of RE generation in the aggregate primary energy supply, an important consideration is the employment generation potential of RE based power capacity. In fact, Jain and Patwardhan (2013), who analyze the employment effects of RE targets, claim that RE technologies create more jobs per unit of installed capacity and per unit of power generated than FE technologies. While not doing any comparisons with FE, our analysis here aims to estimate the direct employment generation from the incremental RE capacity installed, where these capacities are taken as those worked out in Section 3.

This study assesses the number of jobs created due to diffusion of solar (separately for ground-mounted and rooftop solar PV plants) and wind power projects in India. For working out the shares of solar PV and wind, we assume the proportions of incremental capacities and jobs created per unit capacity to be those assumed by CEEW and NRDC (2017) (see Table 15). According to CEEW and NRDC (2017), the job years include those for business development, design and pre-construction, construction and commissioning, and operations and maintenance. The specific values used are also compiled in Table 15 below.

Table 15: Assumptions used for solar and wind capacity shares and job-years by type of technology

RE Technology	Shares in total capacity	Job years/ MW
Ground mounted solar PV	0.375	3.45
Rooftop solar PV	0.25	24.72
Wind	0.375	1.27

Source: CEEW and NRDC (2017)

Using these values, with the shares across different RE technologies remaining unchanged over the years of forecasting, we obtain the following direct job generation potential for India (see Tables 16 to 18). The incremental jobs by 2022 amount to 286 thousand, 311 thousand and 251 thousand in BAU, OPT and PES scenarios. In 2032, these are expected to rise to 1409 thousand, 1533 thousand and 978 thousand respectively under the three cases. In 2042, the cumulative job creation levels rise to 3985 thousand, 4520 thousand and 2054 thousand in case of BAU, OPT and PES respectively.

Table 16: Incremental and cumulative job creation under business-as-usual (BAU) scenario ('000 jobs)

Year	Incremental employment in ground mounted solar	Incremental employment in rooftop solar	Incremental employment in wind	Cumulative (solar + wind)
2022	47	223	17	286
2032	110	527	41	1409
2042	253	1207	93	3985

Source: Authors' calculations

Table 17: Incremental and cumulative job creation under optimistic scenario ('000 jobs)

OPT				
Year	Incremental employment in ground mounted solar	Incremental employment in rooftop solar	Incremental employment in wind	Cumulative (solar + wind)
2022	51	242	19	311
2032	121	577	44	1533
2042	295	1411	109	4520

Source: Authors' calculations

Table 18: Incremental and cumulative job creation under pessimistic scenario('000 jobs)

PES				
Year	Incremental employment in ground mounted solar	Incremental employment in rooftop solar	Incremental employment in wind	Cumulative (solar + wind)
2022	41	195	15	251
2032	65	312	24	978
2042	96	457	35	2054

Source: Authors' calculations

Notably, the specific variable pertaining to unemployment that we have considered for estimating the ARDL equation (in section 3) is the *rate* of unemployment in the economy (defined as UNEMP). Unfortunately, despite much effort, we did not get a consistent time series on the *level* of unemployment, or the number of unemployed people, for the Indian macro-economy for the 27 years over which our analysis spans. We were, thus, unable to measure the macro-level (net) job creating potential of RE for India. Nevertheless, the analysis presented here will be useful to policymakers in estimating the employment potential of RE generation, subject to the proviso that these numbers may not necessarily be incremental. For the latter, a more extensive, economy wide general equilibrium analysis is required, which was outside the scope of research accomplished here.

5. RE diffusion and energy security in India

RE penetration is likely to positively influence the security of India's energy-economy by diversifying the energy basket, reducing the reliance on energy imports, and contributing to an affordable and decentralized energy supply source, with a higher potential for energy access in remote locations. In what follows, we take the time series of many indicators/ dimensions, including some that have been drawn from the forecasting exercise in Section 5, to work out a composite index of energy security. The data span the time period 2017-2042, on a yearly basis. The key variables included in the construction of this index are: market liquidity, share of RE_02 in TPES_01 (total primary commercial energy supply), share of NET_EN_IMP in TPES_01, Herfindahl-Hirschman market concentration index of energy import supplies to India (H-H index), POP_ACCESS_PERCENT and EN_OUT by MNRE, as a share of total energy outlay by the government. The brief discussion on the method of construction of the composite index is provided below, while detailed steps can be found in Appendix F.

5.1 Constructing the energy security index (ESI) using the distance-based approach

To discern the future of energy security for India, given the potential rise in energy demand, we compute the ESI for India under the alternative scenarios and compare them across these.

We employ the distance-based methodology (as in Sarma, 2012) in order to compute a comprehensive index of energy security. The distance-based approach works as follows. In general, suppose, there exist p dimensions or indictors that capture energy security (some of which are mentioned above), each denoted by $X_{i\_n}; i = 1(1)p$ (where p is a finite integer), a normalized ESI could be expressed as a mapping from a p-dimensional real space to a 1-dimensional real space. That is,

$$ESI: \mathbb{R}_{+}^{p} \rightarrow \mathbb{R}_{+}^{1},$$

where

$$ESI = g(X_{1\_n}, X_{2\_n}, \dots, X_{p\_n}); g'(X_{i\_n}) > 0 \;\&\; ESI \in [0, 1].$$

A value of ESI of 0 means no energy security, while a value of 1 means complete energy secured. An increase in ESI over time implies that India is becoming more secure in terms of its energy supply. For more details on the methodology, please refer to Appendix F.

5.2 Data and implications

The index is constructed for the period 2017-42. We use either 6 or 5 indicators to capture energy security. These are just by way of capturing the sensitivity of ESI to the choice of indicators. The specific variables are: market liquidity, share of RE_02 in TPES_01, NET_EN_IMP to TPES_01 ratio, Herfindahl-Hirschman market index of energy imports to India (H-H index), POP_ACCESS_PERCENT and EN_OUT by MNRE. The data sources for each are provided in Table 19 below:

Table 19: Data sources for variables used in calculation of ESI

Variable	Data source
Market liquidity	World Bank database
Share of RE_02 in TPES_01	International Energy Agency statistics
NET_EN_IMP to TPES_01	International Energy Agency statistics
Herfindahl-Hirschman market concentration index of energy imports to India (H-H index)	Calculated from UN COMTRADE database
POP_ACCESS_PERCENT	World Bank database
EN_OUT by MNRE, as a share of total energy outlay by the government	Union Budget documents; Database on Indian Economy, Reserve Bank of India

The plausible structure and implication of each of these dimensions are now discussed.

Basically, market liquidity implies the ratio of net imports of fuel to total imports by the world divided by the same ratio for India. Clearly, a rise in market liquidity implies greater energy security and vice versa. The assumption on this variable is taken to be the same across all the three scenarios – BAU, Optimistic and Pessimistic.

The share of RE_02 in TPES_01 is the calculated share of RE generated in the basket of total primary commercial energy supply. Given its indigenous supply and growing affordability, it is assumed that the rise in the share of RE generation would ensure greater energy security. This variable does not need normalization, since it is a proper fraction. Moreover, it changes according the scenario of RE diffusion estimated by us in Section 3.

The ratio of net energy imports to TPES_01 refers to the proportion of net commercial energy imports in the basket of total primary commercial energy supply. This variable also does not need normalization, as it is a proper fraction. As one would expect, a rise in this share has a negative impact on energy security, as the reliance on imports of energy grows. Hence, we subtract this share from unity in order to ensure its movement in the same direction as energy security. This variable is also assumed to vary across the three scenarios.

The Herfindahl-Hirschman market concentration index is a measure of diversification in terms of global suppliers of energy imports to India. It varies between 0 and 1, and a value close to 1 implies a higher concentration in the suppliers of energy to India, while a value close to 0 implies diversified supplies. Thus, a fall in its value implies greater market diversification and, hence, greater energy security. Accordingly, we subtract this share from unity in order to ensure its movement in the same direction as energy security. This variable does not need normalization since it is a proper fraction. Moreover, the value of this variable remains unchanged across the three scenarios.

The percentage of population with access to electricity is also assumed to be the same across the different scenarios. A rise in this percentage ensures greater security in terms of energy access. This variable too does not need normalization since it is a proper fraction.

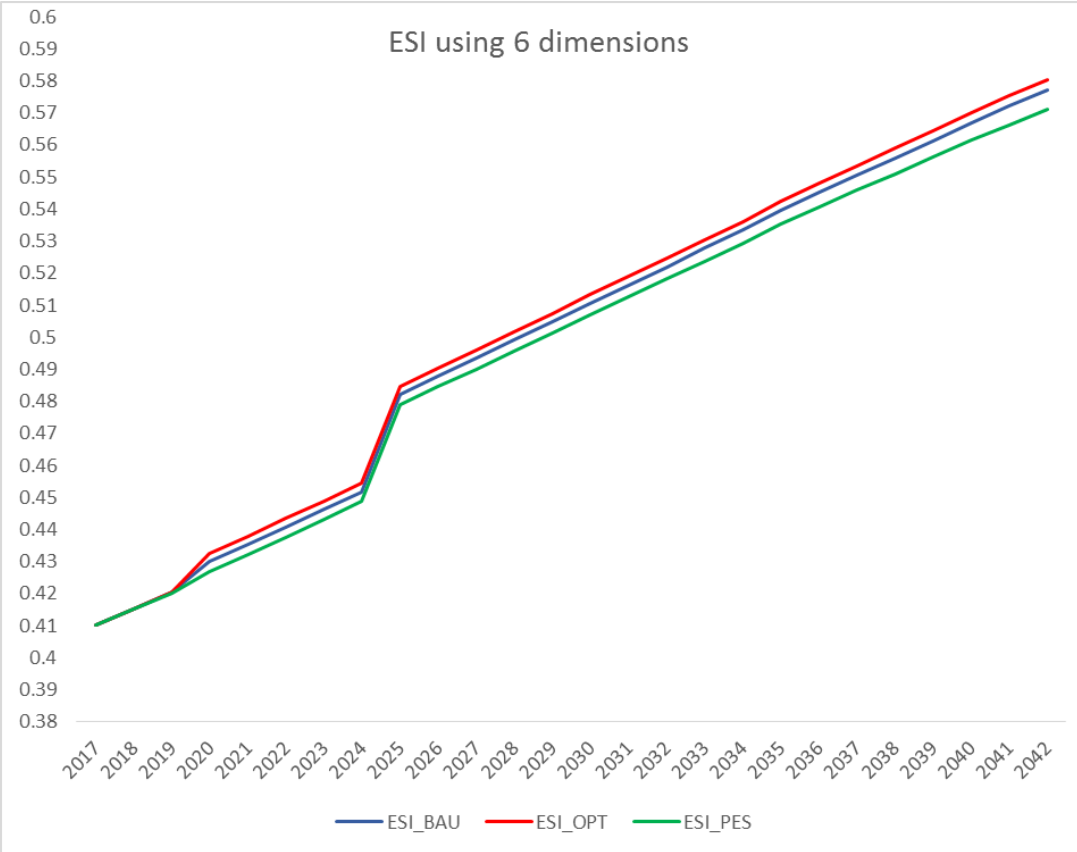
The energy outlay share is also assumed to remain the same across the three scenarios. This captures the share of expenditure by MNRE, Government of India, in total energy outlay by the government. As expected, a higher energy outlay on RE implies a higher share of RE in total energy supply, and this will have a positive impact on energy security. This variable does not need normalization since it is a proper fraction.

Using the above indicators, and the methodology alluded to above and detailed in Appendix F, the ESI is calculated for each of the three scenarios – BAU, Optimistic and Pessimistic. The results are discussed in the following section.

5.3 Estimates of ESI

The energy security index is normalized in a manner as to lie within the range of 0 and 1. The way in which the various dimensions have been combined, a value closer to 1 denotes a higher level of energy security, while a value closer to 0 implies lower energy security. We use two specifications, one with 6 dimensions and the other with 5 dimensions or indicators. In the latter case, of the variables discussed above, we drop market liquidity and re-compute the index. We observe the time trend of ESI under each of the scenarios in the Figures 5 and 6 below.

Figure 4: ESI constructed using 6 dimensions



Source: Authors' calculations

The estimated values of ESI with 6 dimensions is tabulated below.

Table 20: Estimated ESI using 6 dimensions

Year	ESI_BAU	ESI_OPT	ESI_PES
2022	0.440685	0.443422	0.437623
2027	0.493378	0.496057	0.490084
2032	0.522039	0.524785	0.518201

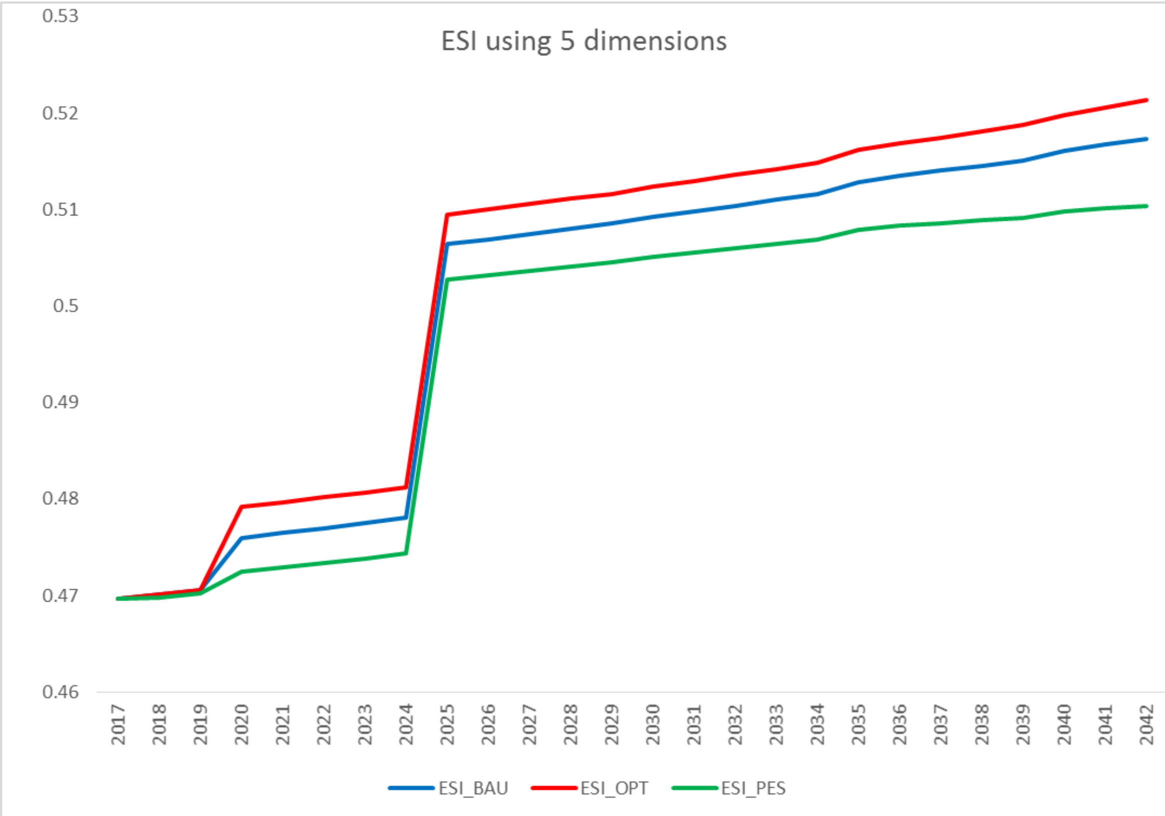
2037	0.550604	0.553555	0.54589
2042	0.577209	0.580539	0.571147

Source: Authors' calculations

As can be seen, the ESI monotonically rises under each scenario. The values are the highest in the case of the Optimistic scenario, followed by the BAU case and the Pessimistic scenario. In the year 2022, ESI is approximately 0.44, under the BAU and the Optimistic scenarios. In comparison, it is a bit lower, at 0.43, under the Pessimistic scenario. The trend is similar in 2032 and 2042 under each scenario, with the values remaining in a tight band of around 0.57 in 2042 in the Pessimistic case, while a slightly higher value of 0.58 is found for the BAU and Optimistic cases in this year.

In case of the use of 5 dimensions, we have the following observable change in ESI.

Figure 5: ESI constructed using 5 dimensions



Source: Authors' calculations

Table 21: Estimated ESI using 5 dimensions

Year	ESI_BAU	ESI_OPT	ESI_PES
2022	0.476989	0.480172	0.473399
2027	0.507457	0.510551	0.503633
2032	0.510398	0.513584	0.505975
2037	0.51402	0.517476	0.508615
2042	0.517362	0.521309	0.510412

Source: Authors' calculations

In this case, the ESI rises from 0.48 in 2022 to 0.52 in 2042 under the Optimistic scenario. In the year 2042, as earlier, the value is approximately the same under both BAU and Optimistic scenarios. It is somewhat lower, at 0.51, in the case of the Pessimistic scenario. The rise is ESI is steeper in the case of the Optimistic scenario as compared to the other scenarios.

In general, the ESI is found to rise over time, with a higher share of RE in TPES_01 and lower associated net energy imports. However, it is found not to vary too much across the three scenarios, mainly because: first, we have assumed that most of the dimensions or indicators do not change across the three scenarios, and second, an equal weight has been assigned to all the dimensions for calculating the composite index. With the inclusion of a larger set of variables, and by taking differing vector of weights on these dimensions, a greater dispersion in ESI calculated across different scenarios would emerge.

This component of our research provides a comprehensive viewpoint to the policymakers as to how India's energy security is likely to vary in terms of the RE shares, other macro-economic variables, energy trade characteristics and energy access under the different specifications of these variables. This would provide signal on how appropriate policies to make India more energy secure in terms of RE can be implemented.

6. Conclusion and key take-aways

India's energy consumption is expected to rise significantly in the future years. According to India's Energy Outlook, 2015, published by the International Energy Agency, some of these trends are quite overwhelming (IEA/ IEO, 2015). India's total energy demand is expected to be propelled upward by 2040, on account of its sheer economic size, which would grow to more than five-times its current level in terms of aggregate GDP and a population growth that would make it the country with the largest population. Accordingly, IEO/ IEA, 2015, projects India's aggregate energy consumption to more than double by 2040, often registering it as among the highest energy consumption growth countries across the globe.

The growing demand for energy has raised two relevant questions: those pertaining to environmental sustainability and energy security. In the absence of stringent policies to mitigate energy-related emissions of gases, dust and fumes from the power sector, industry and transport, India's air pollution problems loom large. The dependence on imports of conventional energy like coal, oil, natural gas has posed a threat to India's energy security. With substantial potential for growth in per capita consumption as well as emphasis on enhancing overall energy access, India faces the challenge of placating its energy security concerns. Consequently, adoption of tailor-made policies that are aimed to enhance indigenous production as well as encouraging the use of alternative, sustainable and decentralized sources of energy, such as solar and wind, is imminent. Apparently, the recent policy push towards RE and indigenous production of energy substantiate an optimistic scenario for the future of India's energy economy.

The Government of India has an ambitious plan of achieving 175 GW of RE by 2022, of which the break-up proposed across technologies is: 100 GW of solar, 60 GW of wind, 10 GW of biomass and 5 GW of small hydro. This would amount to around 18.9% of aggregate power consumption in India in 2022.

RE (as much as FE) has strong backward and forward linkages with key factors characterizing the macro economy, demographics and the energy economy of India. In light of this, the scope of this research as follows. In the aggregate, we aim to delineate and estimate the quantitative linkages of macro-economic and demographic variables (GDP, population, employment, fiscal deficit, energy imports, energy access, return on capital etc.) with RE deployment in India. These relationships are captured under alternative cases of RE diffusion (linked to the key macro-economic and demographic variables), both in the medium- and long-run time frames. Our analysis utilizes macro-econometrics and time series methods for these estimations. These include tests of stationarity, Granger causality tests and cointegration using an ARDL model structure. Based on the relationships estimated, forecasts of RE generation and associated capacity requirements in the medium- and long-runs are developed under three different scenarios (Business as usual, Optimistic and pessimistic). The research also ascertains the impact of RE diffusion on employment generation in the RE sector, using normative data on job-creation per unit of capacity installed in the solar and wind sectors. Finally, the implication of RE penetration and associated movement of key macro-economic and financial variables and other factors, for India's energy security, is assessed by preparing a composite ESI.

The key results and takeaways from our analysis are as follows:

- The unit-root tests using DF-GLS procedure show that GDP_CONS_01, FIS_DEF, RE_02, TPES_01, NET_EN_IMP and ratio of RE_to_FE_TARIFF are non stationary, i.e., integrated of order one or I(1), while the remianing variables, such as POP, CALL_RATE, UNEMP, EN_OUT and POP_ACCESS_PERCENT are found to be stationary, namely, integrated of order zero or I(0). Thus, we have a mix of I(0) and I(1) variables, requiring the reliance on the ARDL model for estimating the long-run equilibrium relationship among these variables.
- Pair-wise Granger causality tests show that RE_02 Granger causes CALL_RATE, FIS_DEF and RE_02 display a two-way causality. Further, GDP_CONS_01 Granger causes RE_02, RE_02 Granger causes NET_EN_IMP, and there is a two-way causality between RE_02 and RE_TO_FE_TARIFF, RE_02 and POP, and RE_02 and POP_ACCESS_PERCENT. Finally, RE_02 Granger causes UNEMP. These causations help explain later the relationships that are derived from the cointegration ARDL equation.
- The ARDL model estimation points toward an equilibrium cointegrating long-run relationship between RE and key economic variables. The long-run levels of GDP_CONS_01, CALL_RATE and RE_TO_FE_TARIFF are found to be positively associated with the penetration of RE(RE_02), while variables such as FIS_DEF, NET_EN_IMP, POP, POP_ACCESS_PERCENT and UNEMP display a negative relationship with RE(RE_02), penetration in India.
- RE generation (RE_02) is positively related to CALL_RATE. In general, a higher CALL_RATE constitutes either the cost of capital (that may dampen investment in RE) or a return on capital investment (that encourages investment in RE equipment). At the macro-level, the latter effect outweighs the former, implying that RE_02 and CALL_RATE move pro-cyclically.
- RE generation (or RE_02) moves negatively with FIS_DEF. Note that, ARDL captures the co-movement of the macro variables. Here, in the aggregate, a higher FIS_DEF is largely indicative of financial support to FE generation. A higher level of RE penetration is associated with lower fiscal deficit on account of lower share of FE generation.
- RE generation (that is, RE_02) is also positively related to GDP_CONS_01, implying that higher incomes induce a higher willingness to pay for RE or a higher demand for RE, hence, the positive relationship. This could also be because RE is a normal good, implying cleaner energy is demanded more at higher incomes or people shift their energy preferences from conventional fossil energy to cleaner energy with an increase in the income level, thus entailing a pro-cyclical relationship between these two variables.
- RE_02 is found to have a negative relationship with NET_EN_IMP, which is expected. On the average, a higher RE generation is associated with lower energy imports, which in India, have a preponderance of FE. Thus, RE substitutes for FE in the aggregate, implying a counter-cyclical movement between these two variables.
- Interestingly, with aggregate POP, and POP_ACCESS_PERCENT, RE generation (RE_02) has a negative correlation, or that, it moves counter-cyclically. Intuitively, a higher population level or higher access of population to electricity places heavy demand on the economy in terms of demand for energy. Given the limited time series dataset (for 27 years only) and India's excessive dependence on FE, so far, the estimation

shows that both -- higher population or population access to electricity -- tend to dampen RE penetration. This direction of this link may undergo a change as more RE diffusion happens.

- The variables RE_02 and RE to FE tariffs move in a direct manner. This is due to the fact that a higher RE_TO_FE TARIFF implies a more remunerative tariff for RE, entailing higher diffusion of RE technologies.
- RE generation (RE_02) moves counter-cyclically with aggregate UNEMP in the Indian economy. A higher RE diffusion is generally associated with lower unemployment rates, at the economy-wide level.
- Utilizing the ARDL estimated equation in (1), three different scenarios, namely, business as usual (BAU), pessimistic and optimistic are postulated for forecasting different levels of RE penetration in India's energy economy. The forecasts of RE generation and associated RE capacity are made for the years 2017-2042, for each of the three scenarios.
- The growth of RE_02 is found to be the highest under the optimistic (OPT) scenario reaching a value of over 16.13 MTOE in 2022, 45.08 MTOE in 2032 and 115.83 MTOE in 2042. The corresponding capacity levels for RE_02, by assuming plant capacity utilization of 25%, are found to be 86 GW in 2022, 239 GW in 2032 and a whopping 615 GW in 2042. The estimate for the year 2040 is 510 GW, which is closer to the estimates by the NITI Aayog. The share of energy supplied by RE_02 to TPES_01 is found to increase from the prevailing less than 1% to 1.45% in 2022, 2.86% in 2032 and 5.74% in 2042.
- The growth under the BAU is closer to that in OPT in the initial years, but the gap widens over time. RE generation is estimated at a slightly lower 15.56 MTOE in 2022, 42.15 MTOE in 2032 and 103.16 MTOE in 2042. This amounts to a capacity requirement of 83 GW, 224 GW and 548 GW in the respective years, based on the same plant utilization factor values. Moreover, this amounts to a share of RE_02 to TPES_01 (in MTOE) of 1.42% in 2022, 2.75% in 2032 and 5.15% in 2042.
- Under the pessimistic (PES) case, the growth of RE_02 is much slower, both in terms of the energy supplied and capacity installed, as compared to BAU and OPT. It reaches an energy level of 14.71 MTOE in 2022, 31.93 MTOE in 2032 and merely 57.44 MTOE in 2042. The associated capacity installed, assuming the same levels of plant capacity utilization values, will be 78 GW, 170 GW and 305 GW in 2022, 2032 and 2042 respectively. Accordingly, it is estimated, that the share of RE_02 to TPES_01 will be lower at 1.38% in 2022, 2.12% in 2032 and 2.9% in 2042.
- Notably, relative to the official targets of RE capacity of 175 GW by 2022 projected by the government, our estimations show that these are likely to be achieved later in time. This is in consonance with the recent apprehensions expressed in this regard, given the available policy framework moving away from feed-in-tariffs to auctions-based purchases, lack of grid infrastructure and evacuation constraints (Live Mint 2017). Specifically, for instance, we get that these are likely to be achieved during 2029-30 under the BAU, a bit earlier, in 2027-28 under the OPT case, and a lot later, in 2032-33 in the PES scenario.
- Using these values of capacity additions, with the shares across different RE technologies unchanged over the years of forecasting, and relying on norms of job

creation for these technologies, we obtain the following direct incremental job generation potential for India. According to our estimates, the incremental jobs by 2022 amount to 286 thousand, 311 thousand and 251 thousand in BAU, OPT and PES scenarios respectively. In 2032, these are expected to rise to 1409 thousand, 1533 thousand and 978 thousand respectively under the three cases. In 2042, the cumulative job creation levels will rise to 3985 thousand, 4520 thousand and 2054 thousand in case of BAU, OPT and PES respectively.

- To discern the future of energy security for India, given the potential rise in energy demand, we compute the ESI for India under alternative scenarios, by employing the distance-based methodology. We compute a comprehensive index of energy security, by relying on several indicators or dimensions of energy security, namely, market liquidity, share of RE_02 in TPES_01, NET_EN_IMP to TPES_01 ratio, Herfindahl-Hirschman market index of energy imports to India, POP_ACCESS_PERCENT and EN_OUT by MNRE.
- The energy security index is normalized in a manner as to lie within the range of 0 and 1. The way in which the various dimensions have been combined, a value closer to 1 denotes a higher level of energy security, while a value closer to 0 implies lower energy security. We use two specifications, one with 6 dimensions and the other with 5 dimensions or indicators. In the latter case, of the variables discussed above, we drop market liquidity and re-compute the index.
- With the inclusion of 6 dimensions, the ESI monotonically rises under each scenario. The values are the highest in the case of the Optimistic scenario, followed by the BAU case and the Pessimistic scenario. In the year 2022, ESI is approximately 0.44, under the BAU and the Optimistic scenarios. In comparison, it is a bit lower, at 0.43, under the Pessimistic scenario. The trend is similar in 2032 and 2042 under each scenario, with the values remaining in a tight band of around 0.57 in 2042 in the Pessimistic case, while a slightly higher value of 0.58 is found for the BAU and Optimistic cases in this year.
- In the case of 5 dimensions, the ESI rises from 0.48 in 2022 to 0.52 in 2042 under the Optimistic scenario. In the year 2042, as earlier, the value is approximately the same under both BAU and Optimistic scenarios. It is somewhat lower, at 0.51, in the case of the Pessimistic scenario. The rise is ESI is steeper in the case of the Optimistic scenario as compared to the other scenarios.
- In general, the ESI is found to rise over time, with a higher share of RE in TPES_01 and lower associated net energy imports. However, it is found not to vary too much across the three scenarios, mainly because we have assumed that most of the dimensions do not change across the three scenarios, and further, there is an equal weight assigned to all the dimensions for calculating the composite index. With the inclusion of a larger set of variables, and varying the vector of weights on these dimensions, a larger dispersion in ESI calculated across different scenarios would emerge.

Further, the outcomes of our research have significant policy implications, as explained below:

The study points out the key macroeconomic factors in terms of how they are linked with RE penetration in India. The study finds that RE diffusion in India is positively associated with

GDP_CONS, CALL_RATE and RE_TO_FE_TARIFF and negatively associated with FIS_DEF, NET_EN_IMP, POP, POP_ACCESS_PERCENT and UNEMP. These entail significant policy messages, such a higher economic growth rate, a higher return on investment, and more remunerative RE tariff would spur RE growth. Alternatively, a higher fiscal deficit, and energy imports will dampen RE diffusion. Similarly, on the grounds of policy implications for India, a case can be made for the fact that a higher level of population, or higher share of population in terms of energy access will imply greater reliance on FE rather than RE.

The contribution of RE to the job creation potential is assessed in this study using NRDC-CEEW data. Thus, this study will be useful to policymakers in estimating the employment potential of RE generation, subject to the proviso that these numbers may not necessarily be incremental. For the latter, a more extensive, economy wide general equilibrium analysis is required.

The research also estimates a comprehensive ESI for India under different scenarios. This provides a broad viewpoint to the policymakers as to how India's energy security varies in terms of RE shares, other macro-economic variables, energy trade characteristics and energy access under the different specifications of these variables. This would provide signals on which appropriate policies to make India more energy secure in terms of RE can be implemented.

7. References and bibliography

Aggarwal, M. & Bhaskar, U. (2017). Dollar-denominated Tariffs Attract Indian Solar Power Firms to South-East Asia. Live Mint, 02 August 2017.

Akashi, O., Hanaoka, T., Masui, T., & Kainuma, M. (2014). Halving global GHG emissions by 2050 without depending on nuclear and CCS. *Climatic change*, 123(3-4), 611-622.

Anger, A. (2010). Including Aviation in the European Emissions Trading Scheme: Impacts on the Industry, CO_2 Emissions and Macroeconomic Activity in the EU. *Journal of Air Transport Management*, *16*(2), 100-105.

Apergis, N., & Payne, J. E. (2012). Renewable and Non-renewable Energy Consumption-growth nexus: Evidence from a panel error correction model. Energy Economics, 34(3), 733-738.

Basu, S. N., Karmakar, A., & Bhattacharya, P. (2015). Growth of Solar Energy in India – Present Status and Future Possibilities. *International Journal of Electrical, Electronics and Computer Systems*, 3(5), 27-32.

Beaudreau, B.C. (2005). Engineering and Economic Growth. Structural Change and Economic Dynamics, 16, 211–220.

Council on Energy, Environment and Water (CEEW) and Natural Resources Defense Council (NRDC) (2012). Laying the Foundation for a Bright Future: Assessing Progress under Phase 1 of India's National Solar Mission. EEW & NRDC. Online at: http://www.nrdc.org/international/india/files/layingthefoundation.pdf

CEEW and NRDC (2015). Clean Energy Powers Local Job Growth in India. http://shaktifoundation.in/wp-content/uploads/2014/02/NRDC-CEEW-Report-India-CleanEnergyJobs-Feb-20151.pdf

CEEW and NRDC (2017). Greening India's Workforce: Gearing up for Expansion of Solar and Wind Power in India. http://ceew.in/pdf/CEEW%20NRDC%20%20Greening%20India's%20Workforce%20report%2020Jun17.pdf

Central Electricity Authority (2016). http://www.cea.nic.in/reports/monthly/installedcapacity/2016/installed_capacity-03.pdf. Downloaded on August 23, 2017.

Dagoumas, A. S., & Barker, T. S. (2010). Pathways to a Low-carbon Economy for the UK with the macro-econometric E3MG model. *Energy Policy*, *38*(6), 3067-3077.

Deb, K. & Appleby, P. (2015). India's Primary Energy Evolution: Past Trends and Prospects. India Policy Forum 2015, National Council of Applied Economic Research, New Delhi.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366a), 427-431.

Dinda, S. (2004). Environmental Kuznets Curve Hypothesis: a survey. Ecological economics, 49(4), 431-455.

Draft National Energy Policy, *India: NITI Aayog, GoI, New Delhi,* http://niti.gov.in/writereaddata/files/new_initiatives/NEP-ID_27.06.2017.pdf.

Elliott, G., T. J. Rothenberg, and J. H. Stock. 1996. Efficient Tests for an Autoregressive Unit Root. *Econometrica*, 64:813–836.

Erdal, G., Erdal, H., Eseng ¨un, K., 2008. The Causality Between Energy Consumption and Economic Growth in Turkey. *Energy Policy*, 36 (10), 3838–3842.

Fuller, Wayne A. (1976), *Introduction to Statistical Time Series*, New York: John Wiley & Sons.

Garces, E., & Daim, T. U. (2012). Impact of Renewable Energy Technology on the Economic Growth of the USA. Journal of the Knowledge Economy, 3(3), 233-249.

Garg, A., Ghosh, D., & Shukla, P. R. (2001). Integrated Energy and Environment Modelling System and Application for India. OPSEARCH-NEW DELHI, 38(1), 3-26.

Glasure, Y.U., 2002. Energy and National Income in Korea: Further Evidence on the Role of Omitted Variables. *Energy Economics* 24, 355–365.

Government of India (2017). NITI Aayog. Draft National Energy Policy. Version as on 27.06.2017.

Government of India (2015). NITI Aayog. Report of the Expert Group on 175 GW RE by 2022.

Government of India (2006) Report of the Working Group on R&D for the Energy Sector for the Formulation of the Eleventh Five Year Plan (2007-2012). http://www.dst.gov.in/about_us/11th-plan/rep-csir.pdf

Government of India (2015). Annual Report 2014-15. Ministry of Petroleum and Natural Gas, New Delhi.

Government of India (2017). Ministry of Statistics and Programme Implementation. Accessed November 30, 2016, URL: http://statisticstimes.com/economy/gdp-growth-of-india.php

Government of India (2006). National Energy Map for India: Technology Vision 2030. The Energy and Resources Institute, Office of the Principal Scientific Advisor.

Government of India (2015). Renewable Energy in India: Growth and Targets. Ministry of New and Renewable Energy, New Delhi.

Government of India (2016). Report of the 5th meeting of the Interim Administrative Cell of International Solar Alliance, Ministry of New and Renewable Energy, New Delhi.

Government of India (2015). Sector Specific Insights Part III: Renewable and Clean Energy, India Energy Security Scenarios Version 2.0 2047, NITI Aayog.

Greene, W. H. 2008. *Econometric Analysis*. 6th ed. Upper Saddle River, NJ: Prentice–Hall.

Gujarati, D. N. (2004). *Basic econometrics*. The McGraw– Hill.

Gunatilake, H., Roland-Holst, D., & Sugiyarto, G (2014). Energy Security for India: Biofuels, Energy Efficiency and Food Productivity. Energy Policy, 65, 761-767.

Integrated Energy Policy: Report of the Expert Committee, (2006) Planning Commission.

Intergovernmental Panel on Climate Change. (2015). *Climate change 2014: mitigation of climate change* (Vol. 3). Cambridge University Press.

International Energy Agency (IEA) Statistics. http://www.iea.org/statistics/statisticssearch/report/?country=INDIA&product=balances&year

Interim Report on 'A Sustainable Development Framework for India's Climate Policy', Centre for Science, Technology and Policy (CSTEP), Karnataka.

IEA/ IEO, International Energy Agency. (2015). *India Energy Outlook*. World Energy Outlook Special Report, France.

Jain, M., & Patwardhan, A. (2013). Employment Outcomes of Renewable Energy Technologies: Implications of Policies in India. *Economic & Political Weekly*, 16, 84-89.

Johansen, S. (1988). Statistical Analysis of Cointegration Vectors. *Journal of Economic Dynamics and Control,* 12: 231–254.

Johansen, S. (1991). Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. *Econometrica*, 59: 1551–1580.

Kale, R. V., & Pohekar, S. D. (2014). Electricity Demand and Supply Scenarios for Maharashtra (India) for 2030: An application of long range energy alternatives planning. *Energy Policy*, *72*, 1-13.

Kainuma, M., Matsuoka, Y., & Morita, T. (2000). The AIM/end-use Model and its Application to Forecast Japanese Carbon Dioxide Emissions. European Journal of Operational Research, 122(2), 416-425.

Koljonen, T., & Lehtilä, A. (2012). The Impact of Residential, Commercial, and Transport Energy Demand Uncertainties in Asia on Climate Change Mitigation. *Energy Economics*, 34, S410-S420.

Kumar, A., Kumar, K., Kaushik, N., Sharma, S., & Mishra, S. (2010). Renewable Energy in India: Current Status and Future Potentials. *Renewable and Sustainable Energy Reviews*, 14(8), 2434-2442.

Lee, C.C., Chang, C.P. (2005). Structural Breaks, Energy Consumption, and Economic Growth Revisited: Evidence from Taiwan. *Energy Economics,* 27, 857–872.

Lehr, U., Lutz, C., & Edler, D. (2012). Green Jobs? Economic Impacts of Renewable Energy in Germany. *Energy Policy*, 47, 358-364.

Live Mint (2017). Renewable Energy Future Hinges on Policy Execution. Live Mint E-paper. December 28, 2017. http://www.livemint.com/Money/vd9N429itd0KUjcFb7NxoM/Renewable-energy-future-hinges-on-policy-execution.html

Loulou, R., & Labriet, M. (2008). ETSAP-TIAM: the TIMES Integrated Assessment Model Part I: Model Structure. *Computational Management Science*, 5(1-2), 7-40.

McPherson, M., & Karney, B. (2014). Long-term Scenario Alternatives and their Implications: LEAP Model Application of Panama' s Electricity Sector. *Energy Policy*, *68*, 146-157.

Mehra, Meeta K. and Pandey, Rita (2017). Emerging Experience with Design and Implementation of Policy Instruments for RET D&D across Countries. In *The Economics of China and India: Cooperation and Conflict. Volume 3: Economic Growth, Employment and Inclusivity: The International Environment.* Agarwal, Manmohan, Wang, Jing and Whalley, John (Eds.). World Scientific.

Ministry of New and Renewable Energy (MNRE) (2012) "Generation of Power under JNNSM." (August). Online at: http://pib.nic.in/newsite/pmreleases. aspx?mincode=28

Mytrah Energy Limited. (2015). Renewable Energy's Transformation of the Indian Electricity Landscape.

NAPCC, Government of India (2008). National Action Plan on Climate Change. Prime Minister's Council on Climate Change.

Nayar, R. (2016). Enforcing Renewable Purchase Obligations. *Economic and Political Weekly*, 40, 21-23.

Nair, R., Shukla, P. R., Kapshe, M., Garg, A., &Rana, A. (2003). Analysis of Long-term Energy and Carbon Emission Scenarios for India. *Mitigation and Adaptation Strategies for Global Change*, *8*(1), 53-69.

NITI Aayog, Government of India (GoI) (2015) A Report on Energy Efficiency and Energy Mix in the Indian Energy System (2030) Using India Energy Security Scenarios, 2047, India: NITI Aayog, GoI, New Delhi,http://niti.gov.in/content/report-energy-efficiency-and-energy-mix-indian-energy-system-2030-using-india-energy.

NITI Aayog and Institute of Energy Economics, Japan (IEEJ) (2017). Energizing India. NITI Aayog, Government of India.

Omri, A. (2014). An International Literature Survey on Energy-Economic Growth Nexus: Evidence from Country-specific Studies. *Renewable and Sustainable Energy Reviews*, 38, 951-959.

Onafowora, O. A., & Owoye, O. (2015). Structural Vector Auto Regression Analysis of the Dynamic Effects of Shocks in Renewable Electricity Generation on Economic Output and Carbon Dioxide Emissions: China, India and Japan. International Journal of Energy Economics and Policy, 5(4).

Pandey, R. (2002). Energy Policy Modelling: Agenda for Developing Countries. *Energy Policy*, 30(2), 97-106.

Pandey, R. (1998). Integrated Energy Systems Modelling for Policy Analysis and Operational Planning. Unpublished doctoral dissertation, Indian Institute of Management, Ahmedabad, India.

Pandey, Rita and Mehra, Meeta K. (2017). Choice and Design of Policy Instruments towards Promoting Renewable Energy Technologies: Conceptual Framework and Guiding Principles. In *The Economics of China and India: Cooperation and Conflict*. *Volume 3: Economic Growth, Employment and Inclusivity: The International Environment*. Agarwal, Manmohan, Wang, Jing and Whalley, John (Eds.). World Scientific.

Parihar, R. (2012). "Congress Gets Burned by the Sun: Rajasthan Government Issue Fraud Certificates to Congress MP for Solar Projects." India Today. (March 26). Online at: http://indiatoday.intoday.in/story/

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds Testing Approaches to the Analysis of Level Relationships. *Journal of Applied Econometrics*, *16*(3), 289-326.

Proença, S., & Aubyn, M. S. (2013). Hybrid Modeling to Support Energy-climate Policy: Effects of Feed-in-tariffs to Promote Renewable Energy in Portugal. *Energy Economics*, *38*, 176-185.

Rajesh, N., Shukla, P. R., Kapshe, M., Garg, A., & Rana, A. (2003). Analysis of Long-term Energy and Carbon Emission Scenarios for India. Mitigation and Adaptation Strategies for Global Change, 8(1), 53-69.

REN21 (2013). Renewables 2013 Global Status Report. Paris: REN21 Secretariat.

REN21 (2014). Renewables 2014 Global Status Report. Paris: REN 21 Secretariat

Roinioti, A., Koroneos, C., & Wangensteen, I. (2012). Modeling the Greek Energy System: Scenarios of Clean Energy Use and their Implications. *Energy Policy*, 50, 711-722.

Sarma, M. (2012). Index of Financial Inclusion–A Measure of Financial Sector Inclusiveness. *Berlin (GE): Berlin Working Papers on Money, Finance, Trade and Development*.

Sari, R., & Soytas, U. (2007). The Growth of Income and Energy Consumption in Six Developing Countries. *Energy Policy*, 35(2), 889-898.

Seebregts, A. J., Goldstein, G. A., & Smekens, K. (2002). Energy/Environmental Modeling with the MARKAL Family of Models. In *Operations Research Proceedings 2001* (pp. 75-82). Springer Berlin Heidelberg.

Shahbaz, M., Zeshan, M., & Tiwari, A. K. (2015). Analysis of Renewable and Non-renewable Energy Consumption, Real GDP and CO_2 Emissions: A structural VAR approach in Romania. Bulletin of Energy Economics (BEE), 3(3), 105-118.

Shukla, P. R., & Kanudia, A. (1997). Future Energy and Greenhouse Gas Emissions from India: Modelling and Analysis. Energy Strategies and Greenhouse Gas Mitigation, Allied Publishers Limited, New Delhi, India, 5.

Silva, S., Soares, I., & Pinho, C. (2012). The Impact of Renewable Energy Sources on Economic Growth and CO_2 Emissions - an SVAR Approach. European Research Studies, 15(4), 133.

Stern, D.I., Cleveland, C.J. (2003). Energy and Economic Growth. Rensselaer Working Papers in Economics 0410.

Stern, D.I. (1993). Energy and Economic Growth in the USA. A multivariate approach. *Energy Economics,* 15, 137–150.

Stern, D.I. (1997). Limits to Substitution and Irreversibility in Production and Consumption: a Neoclassical Interpretation of Ecological Economics. *Ecological Economics*, 21, 197–215.

Stern, D.I. (2000). A Multivariate Cointegration Analysis of the Role of Energy in the US Macroeconomy. *Energy Economics,* 22, 267–283.

Three Year Action Agenda 2017-18 to 2019-20. India: NITI Aayog, GoI, New Delhi,http://niti.gov.in/writereaddata/files/coop/ActionPlan.pdf.

Tiwari, A. K. (2011). A Structural VAR Analysis of Renewable Energy Consumption, Real GDP and CO_2 emissions: Evidence from India. *Economics Bulletin*, *31*(2), 1793-1806.

Trading Economics (https://tradingeconomics.com/india/unemployment-rate/forecast, accessed on 13th July 2017)

The Electricity Act (2003), Legislative Department, Ministry of Law and Justice.

The Electricity (Amendment) Bill (2014).

UN COMTRADE database, https://comtrade.un.org/, accessed on 28th November 2017.

Union Budget documents, Expenditure of Ministries and Departments, http://indiabudget.nic.in/, accessed on December 10, 2017.

Wei, M., Patadia, S., & Kammen, D. M. (2010). Putting Renewables and Energy Efficiency to Work: How Many Jobs Can the Clean Energy Industry Generate in the US? *Energy Policy*, *38*(2), 919-931.

Wianwiwat, S., & Asafu-Adjaye, J. (2013). Is There a Role for Biofuels in Promoting Energy Self Sufficiency and Security? A CGE Analysis of Biofuel Policy in Thailand. *Energy Policy*, *55*, 543-555.

World Bank, World Development Indicators (WDI). https://data.worldbank.org/data-catalog/world-development-indicators ; downloaded on September 10, 2017.

World Wildlife Fund (WWF) and World Resources Institute (WRI) (2013). Meeting Renewable Energy Targets: Global Lessons from the Road to Implementation. http://awsassets.panda.org/downloads/meeting_renewable_energy_targets__low_res_.pdf

Appendix A: Review of Modeling Approaches to Understand the Energy Economy Linkages

The policy push towards RE generation in India has aimed to ensure uninterrupted and reliable supply of cleaner energy for meeting its economic growth targets. Apart from economic growth, it is pertinent to unravel the prospect of RE generation for creating employment opportunities, reducing import-dependence, mitigating balance of payment woes, and meeting emissions targets. Resultantly, energy projections for future serve as a blueprint for the current and prospective policy thrust. Research in energy economics has used a motley of techniques in order to project future energy scenarios. In general, energy modeling may employ top-down models, bottom-up models, computable general equilibrium models or time series macro-econometric modeling. Among these, the bottom-up optimization models have been traditionally used by developing economies (Pandey, 2002). The bottom-up approaches provide future energy balances that can be utilized as inputs in the top-down models (Garg et al., 2001). These also allow capturing the impacts of newer technology and changes in fuel-mix within a sector by incorporating fuel flows and technological linkages. In the following section, we explore each of these alternative energy policy modeling techniques.

A.1. Models based on optimization techniques

Optimization models have been the most commonly used ones that help determine the optimal energy-mix that minimizes technology costs, given supply constraints, energy prices and end-use sectoral demands. This class of models includes the MARKAL (Market Allocation) model, the AIM/end-use model (Asia-Pacific Integrated Model) and the TIMES model (an evolution of MARKAL). While the MARKAL model has been set up for the overall energy system analysis, AIM/ end-use model selects the technology mix within each end-use sector so as to minimize technology costs (Garg et al., 2001).

A.1.1. MARKAL

A dynamic linear programing model based on the bottom-up approach, MARKAL takes into account the entire life cycle of a resource, beginning from the point of extraction to the point of end-use. It also accounts for technology efficiencies, conversion and transmission losses, transportation costs, etc. This model was developed by the Energy Technology Systems Analysis Program (ETSAP) of the International Energy Agency (IEA) (Seebregts et al., 2002). Being a linear programming model, MARKAL optimizes a linear objective function subject to a set of linear constraints. The problem is to identify the optimum activity levels of processes that satisfy the constraints at minimum cost. These constraints include primary energy availability, access to certain technology, emissions standards, etc.

The elements of MARKAL simulate the flow of energy in various forms like energy carriers involved with primary energy supplies (e.g., mining, petroleum extraction, etc.), conversion and processing (e.g., power plants, refineries, etc.), and end-use demand for energy services (e.g., boilers, automobiles, residential space conditioning, cooking etc.). The demand for energy services can be disaggregated by sector or by functions within each sector (Seebregts et al., 2002). Through optimization, the model helps in selecting from each of the energy sources, energy carriers, and conversion technology the least cost resource/ fuel/ technology mix subject to the constraints. Any defined specification of new technology/ cleaner technology (i.e., less carbon intensive) helps in identifying the total energy system costs, changes in fuel and technology mix, and levels of pollution emissions.

The National Energy Map for India: Technology Vision 2030, prepared by The Energy and Resources Institute, New Delhi, for the Government of India (GoI, 2006) uses the MARKAL formulation in order to forecast energy demand for India. With a forecasting timespan of 35 years, from 2001-2036, the model disaggregates the demand side of the energy economy into five major energy consuming sectors, namely, agriculture, commercial, industry, residential and transport. In order to capture the end-use demands within sectors, intra-sector disaggregation is done. The supply side incorporates both domestic and foreign supplies of conventional energy sources like coal, oil, natural gas, nuclear power as well as renewables like solar, wind, biomass, and small-hydro. Apart from these, various conversion and process technologies characterized by their respective investment costs, operational expenditure, and technical efficiency are also incorporated in the model. The MARKAL approach has also been used by Kanudia and Loulou (1996), Shukla et al. (1997) and Pandey (1998) in order to estimate future energy scenario in India.

A.1.2. AIM/END-USE MODEL

The AIM/end-use model comprises an energy analysis system that connects energy supply with energy service demands and links them with technological information about service technologies (Kainuma et al., 2000). The system has four components, namely, external energy services, service technologies, internal energy and final energy services. The final energy services demands are estimated based on socioeconomic indicators like population, economic growth and industrial structure. The framework minimizes discounted energy system costs at the end-use sub sector level (Deb and Appleby, 2015). Despite similarities with the MARKAL system, the AIM model goes into more details to explain intra-sectoral energy demands.

Akashi et al. (2014) use the end-use model in order to forecast greenhouse gas emissions in a multi-regional framework, including India, which has been included in The Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2015).

A.1.3. TIMES

The basic framework, in this case, remains the same as it also chooses a technology mix that minimizes the discounted value of technology cost subject to a set of constraints. The TIMES model has been described as a reincarnation of MARKAL approach with a set of new features like variable length periods, vintage technologies, detailed representation of cash flows, technologies with flexible inputs and outputs, stochastic programming with risk aversion, climate module, endogenous energy trade between regions (Loulou et al., 2007). Koljonen et al. (2012) uses this framework to study the transition to low carbon energy systems in India, China and South-East Asia with special focus on residential, commercial and transport sectors.

A.2. E3ME and LEAP models

E3ME is a computer-based model of the world's economic and energy systems and the environment. It was developed originally through the European Commission's research framework programs, and is now extensively used worldwide for policy assessment, for forecasting and research. E3ME was initially proposed to meet an expressed need of researchers and policy makers for a quantitative framework for the assessment of the impacts of Energy-Environment-Economy (E3) policies. The model was developed to get the short-term and medium-term economic impacts as well as, more broadly, the long-term effects of such policies, such as those from the supply side of the labor market. In an economy, the economic activities undertaken by persons, households, firms and other groups have effects on other groups after a time lag, and the effects continue to have impacts for the upcoming generations, although many of the effects soon become so small as to be insignificant. But, there are many actors and impacts, both favorable and damaging, which accumulate in economic and physical stocks. The effects are transmitted through the environment (with externalities such as greenhouse gas emissions contributing to global warming), through the economy and the price and money systems (via the markets for labor and commodities), and through the global transport and information networks. The markets transmit effects in three main ways: through the level of activity creating demand for inputs of materials, fuels and labor; through wages and prices affecting incomes; and through incomes leading, in turn, to further demands for goods and services. These interdependencies suggest that an E3 model is comprehensive, and includes many linkages between different parts of the economic and energy systems through feedback effects.

Anger (2010), discussed possible effects of the inclusion of the airlines sector in the European Emissions Trading Scheme on the aviation industry in terms of CO_2 emissions and the macroeconomic activity in EU. The analysis employs the Energy–Environment–Economy model for Europe, a dynamic simulation framework, to examine the impacts of the European Emissions Trading Scheme on air transport. The impacts on air transport output and the macroeconomic effects are found to be small. Dagoumas and Barker (2010) examined different carbon pathways for achieving deep CO_2 emissions reduction targets for the United Kingdom (UK) using a macro-econometric hybrid model E3MG, which stands for Energy–Economy–Environment model at the Global level. The E3MG, with UK as one of its regions, takes a top-down approach for modeling the global economy and for predicting the aggregate and disaggregate energy demand and a bottom-up approach (Energy Technology sub-Model, ETM) for simulating the power sector, which then provides feedback to the energy demand equations and the whole economy. Three alternative pathway scenarios simulate CO_2 reduction by 40%, 60% and 80% by 2050 as compared to 1990 levels respectively, and are compared with a reference scenario (REF), with no reduction target.

LEAP, the Long-range Energy Alternatives Planning system, is a popular software tool for energy policy analysis and climate change mitigation analysis developed at the Stockholm Environment Institute. LEAP has been opted for by several organizations in more than 190 countries across the world. It has been employed at many different geographical scales ranging from cities and states to national, regional and global applications. LEAP is fast becoming the de facto standard for countries for undertaking integrated resource planning, greenhouse gas emissions mitigation assessments, and Low Emissions Development Strategies (LEDS), especially in the developing world, and many countries have also chosen to use LEAP as a part of their commitment to report to the UN Framework Convention on Climate Change (UNFCCC).

Roinioti et.al (2012) used LEAP as the main tool in the scenario analysis for modeling the Greek energy system in the scenarios of clean energy use and their implications. Further, LEAP has been used by Kale and Pohekar (2014) to forecast electricity demand for the target year 2030, for the state of Maharashtra, India. Three different scenarios have been considered by them that include Business as Usual (BAU), Energy Conservation (EC) and Renewable Energy (REN). They found that, in the target year 2030, the projected electricity demand for BAU and REN is bigger by 107.3% over the base year 2012 and EC electricity demand has increased by 54.3%. They further found that the estimated values of greenhouse gases for BAU and EC, in the year 2030 to be 245.2% and 152.4% more than the base year, and for REN as 46.2% lower. McPherson and Karney (2014) also forecasted long-term scenario alternatives and their implications using a LEAP model application of Panama's electricity sector.

A.3. Computable General Equilibrium (CGE) models

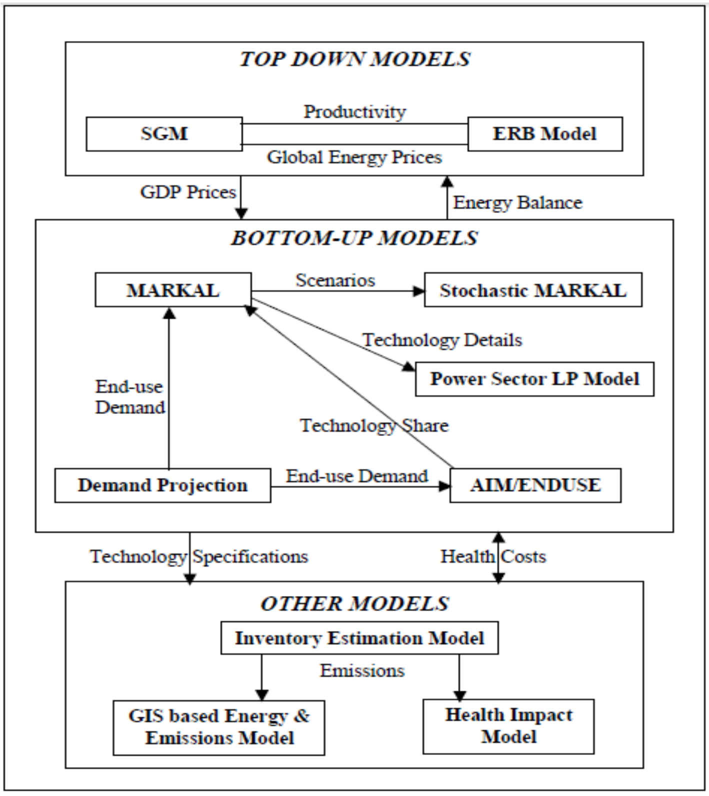
CGE models are a popular tool for quasi-empirical analysis of externalities in the environment as well as policies for mitigating these, which are strong enough to influence prices across multiple markets in the economy. A CGE model is a representation in algebraic form of the abstract Arrow-Debreu general equilibrium framework which is calibrated based on the economic data. The resulting algebraic problem is solved for the supplies, demands and prices that support an equilibrium across a specified set of markets, and which can range from a single sub-national region to multiple groups of countries interacting within the global economy. Each and every economy modeled in CGE framework usually follows the same basic structure: a set of producers, consumers and governments whose activities are related by markets for commodities and factors as well as taxes, subsidies and perhaps other types of economic distortions and policies.

Proenca and Aubyn (2013) checked empirically the impacts of feed-in-tariffs policy to promote electricity generation through RE on the economy and environment for Portugal. They have employed a hybrid top-down/ bottom-up general equilibrium modeling approach, which is a good methodology to analyze the complex interactions between economic, energy, and environmental issues related to energy policies, with feedback effects. The model takes together a bottom-up activity analysis representation of the electricity sector with a top-down CGE model in a unified mathematical framework using the Mixed Complementarity Problem (MCP) format, where the production possibilities in the electricity sector are represented by convex combinations of discrete technological options, and the other production sectors are represented by some top-down aggregate functional forms. The simulation results of the model confirmed the empirical evidence that the feed-in-tariff policy opted by Portugal is both an effective and a cost-efficient way to increase the generation of electricity from RE, and, thus, to achieve the national target of RE based electricity supply of 45% in 2010. Further, results showed a relatively modest macroeconomic impact, indicating potentially low economic adjustment costs, whereas from an environmental perspective, the deployment of RE results in significant carbon emissions reduction. Further, Winwiwat and Asafu-Adjaye (2013) developed a CGE model of the Thai economy that analyzes the government's newly opted RE development plan. This plan aims to increase the domestic energy use from renewable sources to replace fossil fuel imports. The study simulated specific policies and found that encouraging the use of biofuels led to a rapid increase in the price of biofuel and biofuel feedstock in the short-run, whereas these prices tended to rise only slightly in the long-run due to more elastic supplies. The prices of food and other products increased marginally, implying that food security was not diluted by the policy. Gunatilake et.al (2014) examined India's options for managing energy price risk in three ways: biofuel development, energy efficiency promotion, and food productivity improvements. The results of their study suggested that biodiesel shows promise as a transport fuel substitute that can be produced in ways that fully utilize marginal agricultural resources and, hence, promote rural livelihoods. To assess India's policy options with respect to biofuels and food security, they used a global dynamic CGE model calibrated to the Global Trade Analysis Project (GTAP) database. The model was applied to assess different scenarios such as oil price increase, 20% biodiesel standard, 20% bioethanol standard, energy efficiency improvement and food productivity increase and their impact on the macroeconomic variables. Most of the other research that used CGE model in Indian context mainly followed the AIM/ CGE framework discussed in section 2.1.2.

A.4. Integrated Energy Modeling

The energy-economy-emissions mitigation analysis uses an integrated modelling framework, which comprises three modules, namely, top-down models, bottom-up models and local models. Each of these modules are interlinked and are further segregated into multiple individual modules. The outputs of the top-down models, like GDP and energy price projections, are used as exogenous inputs to the bottom-up models. The bottom-up models provide future energy balance output that is used for tuning inputs of the top-down models. The detailed technology and sector level emissions projections obtained from the bottom-up models are used as an input to the Geographical Information System (GIS) based energy and emissions mapping for the country (Nair et al., 2003). GIS (a local model) is used as a tool for regional analysis of energy use and emissions patterns. This may be accompanied by a health impact model which links emissions from energy use in different sectors to the human health (Garg et al., 2001; see Figure A1 below).

Figure A1: Soft-linked integrated modeling framework



Source: Garg et al., 2001

A.5. Time series modeling

Unlike optimization methods, time series macro-econometrics modeling aims to examine any temporal dependence structure between energy demand and/ or supply and economic growth, employment, trade balance, emissions, etc. The existing literature on energy-growth and environment has provided mixed results as far as the temporal association is concerned. Such disparate and equivocal conclusions are a result of diverse methodologies adopted for the studies, different set of countries, different reference periods and datasets, etc. As a result, the literature can be delineated as a set of four testable hypotheses based on the causal links between the variables, namely, the feedback hypothesis, the growth hypothesis, the conservation hypothesis and the neutrality hypothesis (Omri, 2014). The feedback hypothesis states that there exists a bi-directional relationship between energy consumption and economic growth. However, causality may run from energy consumption to economic growth (growth hypothesis). In such scenarios, energy is regarded as a complementary input along with labor and capital stock, for economic growth. The conservation hypothesis establishes a positive uni-directional relationship running from economic growth to energy consumption. Lastly, if there exists no short-run or long-run association between energy consumption and economic growth, then the neutrality hypothesis holds.

Most studies on RE consumption/ generation testify the growth hypothesis, which implies that any shock to the share of RE has a statistically significant impact on economic growth and CO_2 emissions. These studies are broadly based on a Structural Vector Autoregressive (SVAR) Model or a Vector Error Correction Model (VECM). Onafowora and Owoye (2015) find that a positive shock to the share of electricity generated from RE has a positive impact on output in the long-run and reduces CO_2 emissions for countries like India, China and Japan. Similar studies have also been undertaken for countries like USA, Denmark, Portugal and Spain by Silve et al. (2011), only one of which, i.e., for USA, found a positive association running from electricity consumption from renewable sources to GDP. In comparison, any positive shock to RE consumption had a negative impact on GDP in case of Denmark, Portugal and Spain. This has been substantiated by the fact that RE generation entails additional costs in terms of installation, maintenance and fiscal financing of feed-in-tariffs. The burden on the government budget translates into a negative financial impact on the economy.

Another study by Tiwari (2011) on India corroborates the growth hypothesis. This study has used hydroelectricity consumption as a source of RE, and the variance decomposition shows that the share of RE consumption explains a significant part of the forecast error variance of real GDP. Furthermore, any positive shock to real GDP results in a rise in CO_2 emissions.

The afore-mentioned studies have primarily focused on RE sources. The literature also comprises comparative studies on renewables versus non-renewables energy and their impact on economic growth and environmental quality. Both RE and FE sources are incorporated as inputs in the production function and the elasticity of substitution is estimated. The earlier studies have estimated the production function without segregating renewables and non-renewables. These studies reinforce the growth hypothesis and suggest that energy is a relatively more important input than labor or capital in some countries (Sari and Soytas, 2007). Apergis and Payne (2012) is a panel study for 80 countries within a multivariate panel framework over the period 1990–2007. They find a bi-directional relationship between renewables and non-renewables and economic growth both in the short-run and the long-run. The interdependence between both the sources of energy and economic growth reiterates the fact that non-renewables play a key role in driving economic growth and further growth fillips energy consumption. In a country like Romania, the forecasts displayed a feedback relationship, yet the effect of non-renewable energy consumption on economic growth was higher (Shahbaz et. al. 2011). However, the study by Apergis and Payne (2012) found evidence of substitutability between the two sources of energy, thus suggesting that investment in RE generation would mitigate the problem of greenhouse gas emissions.

A remarkable advancement in such comparative studies is the use of endogenous growth models, where technology is endogenously determined by the level of R&D investment. Garces and Daim (2012) disaggregate R&D investment into two components, namely, R&D investment in RE technology and R&D investment in non-renewable energy for USA for the period 1974-2006. The results validate both short-run and long-run temporal association running from R&D investment to economic growth (measured by multi-factor productivity). Furthermore, the effect of non-renewable energy on growth is greater than that of RE, which is quite logical since renewables are not cost competitive and less popular.

So far, the studies have focused on economic growth as the primary macroeconomic indicator. However, researchers have also studied the association between energy use and employment generation. Studies for USA and Germany by Wei et. al. (2009) and Lehr et. al.

(2011) respectively, suggest that the use of non-fossil fuel technologies generate more jobs that fossil fuel-based technologies.

Notwithstanding the role of FE in boosting economic growth due to cost competitiveness and popularity, it is pertinent to consider the additional benefits from RE technology, namely, reduction in fossil fuel usage, improvement in energy efficiency, mitigation of externalities like global warming, climate change and local pollution and health problems, etc. If the national accounting system internalizes these factors, then the contribution of renewables to economic growth would expand. Therefore, RE sector holds a promising position in the field of growth and environmental protection, thereby also contributing toward enhanced energy security prospects.

In view of the aim of this research being an assessment of macroeconomic impacts of RE diffusion and its energy security implications, it is macro-econometric time-series analysis that is used as a method in this research.

Appendix B: Definition of the variables

Variable	**Code**
Renewable energy (Solar, Wind, Biogas)	RE_02
Call rate	CALL_RATE
Gross fiscal deficit	FIS_DEF
Gross domestic product	GDP_CONS_01
Net energy imports	NET_EN_IMP
Percentage of population with access to electricity	POP_ACCESS_PERCENT
Population	POP
Unemployment rate	UNEMP
Relative tariffs (RE to FE)	RE_TO_FE_TARIFF
Market liquidity	MKT_LIQ
Herfindahl-Hirschman index	HH_INDEX
Actual expenditure by the MNRE (Revenue plus capital)	MNRE_EXP

Appendix C: Unit-root tests (DF-GLS)

Unit-root test shows whether the series under consideration is stationary or non-stationary. Stationarity of the series means that its mean, variance and covariance are independent of time. It is appropriate for most of the time-series variables to test whether these have a unit root or not. If a variable contains a unit root at levels, then it is said that the variable is non-stationary at levels. To apply the Granger causality test we need all the variables to be stationary. The pioneering work for unit root test in time-series was done by Dickey and Fuller (Fuller, 1976; Dickey and Fuller, 1979). The basic idea in unit root test is to test the null hypothesis that ρ = 1 in

$$y_t = \rho y_{t-1} + u_t \qquad (C1)$$

Thus, here the hypotheses of interest are "H_0 : series contains a unit root" against "H_1 : series is stationary". In practice, for the ease of computation and interpretation, the above regression equations can be written in the following different form:

$$\Delta y_t = \delta y_{t-1} + u_{t,} \qquad (C2)$$

so that the test of ρ =1 is equivalent to the test of δ =0 (since ρ – 1= δ = 0).

Dickey-Fuller unit root test can be performed allowing for a constant intercept term or an intercept term with a deterministic trend or neither of an intercept or deterministic trend in the regression equation. The regression equation when both intercept and deterministic trend terms are included is as follows:

$$y_t = \alpha + \rho y_{t-1} + \beta t + u_{t.} \qquad (C3)$$

The above equation can be written in a simpler form by subtracting y_{t-1} from both sides, as

$$\Delta y_t = \alpha + \delta y_{t-1} + \beta t + u_t \qquad (C4)$$

However, such the regression in equation (B4) is likely to be plagued by serial correlation if we apply OLS. To get rid of from this problem, the Augmented Dickey-Fuller (ADF) test of the following form is proposed:

$$\Delta y_t = \alpha + \delta y_{t-1} + \beta t + \gamma_1 \Delta y_{t-1} + \gamma_2 \Delta y_{t-2} + \cdots\cdots + \gamma_k \Delta y_{t-k} + u_{t,} \qquad (C5)$$

where "k" is the number of lags specified by some information criterion [Akaike(AIC) or Schwarz].

Now applying OLS in equation (5), the test statistic for H_0 : δ =0 can be obtained by $Z_t = \hat{\delta} / \sigma_\delta$, where σ_δ is the standard error of $\hat{\delta}$.

But the methodology used in this study to get the presence of unit-root of the variables is DF-GLS methodology. It performs the modified Dickey–Fuller t test (known as the DF-GLS test) proposed by Elliott, Rothenberg, and Stock (1996). Basically, the test is an extended version of augmented Dickey–Fuller test, where the time series is transformed via generalized least squares (GLS) regression before performing the test. Elliott, Rothenberg, and Stock (1996), and later some other studies, have shown that this test has significantly greater power over the previous versions of the augmented Dickey-Fuller test.

The detailed unit root test results are now compiled below for each of the variables.

CALL_RATE

Null Hypothesis: CALL_RATE has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic - based on SIC, maxlag=6)

		t-Statistic
Elliott-Rothenberg-Stock DF-GLS test statistic		-3.503797
Test critical values:	1% level	-3.770000
	5% level	-3.190000
	10% level	-2.890000

*Elliott-Rothenberg-Stock (1996, Table 1)

Warning: Test critical values calculated for 50 observations and may not be accurate for a sample size of 26

DF-GLS Test Equation on GLS Detrended Residuals

Dependent Variable: D(GLSRESID)

Method: Least Squares

Date: 12/11/17 Time: 03:42

Sample (adjusted): 1991 2016

Included observations: 26 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GLSRESID(-1)	-0.664146	0.189550	-3.503797	0.0017

R-squared	0.328803	Mean dependent var	0.100950
Adjusted R-squared	0.328803	S.D. dependent var	3.643930

S.E. of regression	2.985349	Akaike info criterion	5.063013
Sum squared resid	222.8077	Schwarz criterion	5.111401
Log likelihood	-64.81917	Hannan-Quinn criter.	5.076947
Durbin-Watson stat	1.753534		

FIS_DEF

Null Hypothesis: FIS_DEF has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic - based on SIC, maxlag=6)

		t-Statistic
Elliott-Rothenberg-Stock DF-GLS test statistic		-1.737438
Test critical values:	1% level	-3.770000
	5% level	-3.190000
	10% level	-2.890000

*Elliott-Rothenberg-Stock (1996, Table 1)

Warning: Test critical values calculated for 50 observations and may not be accurate for a sample size of 26

DF-GLS Test Equation on GLS Detrended Residuals

Dependent Variable: D(GLSRESID)

Method: Least Squares

Date: 12/11/17 Time: 03:42

Sample (adjusted): 1991 2016

Included observations: 26 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GLSRESID(-1)	-0.212905	0.122540	-1.737438	0.0946

R-squared	0.107723	Mean dependent var	-2.135015
Adjusted R-squared	0.107723	S.D. dependent var	523.8757
S.E. of regression	494.8552	Akaike info criterion	15.28411
Sum squared resid	6122041.	Schwarz criterion	15.33250
Log likelihood	-197.6934	Hannan-Quinn criter.	15.29804
Durbin-Watson stat	2.036199		

D(Fiscal-Deficit)

Null Hypothesis: D(FIS_DEF) has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic - based on SIC, maxlag=6)

		t-Statistic
Elliott-Rothenberg-Stock DF-GLS test statistic		-5.905742
Test critical values:	1% level	-3.770000
	5% level	-3.190000
	10% level	-2.890000

*Elliott-Rothenberg-Stock (1996, Table 1)

Warning: Test critical values calculated for 50 observations

and may not be accurate for a sample size of 25

DF-GLS Test Equation on GLS Detrended Residuals

Dependent Variable: D(GLSRESID)

Method: Least Squares

Date: 12/11/17 Time: 03:43

Sample (adjusted): 1992 2016

Included observations: 25 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.

GLSRESID(-1)	-1.185463	0.200731	-5.905742	0.0000

R-squared	0.592342	Mean dependent var	-7.131012
Adjusted R-squared	0.592342	S.D. dependent var	802.1838
S.E. of regression	512.1788	Akaike info criterion	15.35440
Sum squared resid	6295851.	Schwarz criterion	15.40316
Log likelihood	-190.9300	Hannan-Quinn criter.	15.36793
Durbin-Watson stat	2.070189		

GDP_CONS_01

Null Hypothesis: GDP_CONS_01 has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 1 (Automatic - based on SIC, maxlag=6)

		t-Statistic
Elliott-Rothenberg-Stock DF-GLS test statistic		-0.493138
Test critical values:	1% level	-3.770000
	5% level	-3.190000
	10% level	-2.890000

*Elliott-Rothenberg-Stock (1996, Table 1)

Warning: Test critical values calculated for 50 observations

and may not be accurate for a sample size of 25

DF-GLS Test Equation on GLS Detrended Residuals

Dependent Variable: D(GLSRESID)

Method: Least Squares

Date: 12/11/17 Time: 03:43

Sample (adjusted): 1992 2016

Included observations: 25 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GLSRESID(-1)	-0.018215	0.036937	-0.493138	0.6266
D(GLSRESID(-1))	0.876636	0.119055	7.363285	0.0000

R-squared	0.698070	Mean dependent var	329.5183
Adjusted R-squared	0.684942	S.D. dependent var	2323.050
S.E. of regression	1303.928	Akaike info criterion	17.26077
Sum squared resid	39105273	Schwarz criterion	17.35828
Log likelihood	-213.7596	Hannan-Quinn criter.	17.28781
Durbin-Watson stat	2.103579		

D(GDP_CONS_01)

Null Hypothesis: D(GDP_CONS_01) has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 1 (Automatic - based on SIC, maxlag=6)

		t-Statistic
Elliott-Rothenberg-Stock DF-GLS test statistic		-4.200952
Test critical values:	1% level	-3.770000
	5% level	-3.190000
	10% level	-2.890000

*Elliott-Rothenberg-Stock (1996, Table 1)

Warning: Test critical values calculated for 50 observations

and may not be accurate for a sample size of 24

DF-GLS Test Equation on GLS Detrended Residuals

Dependent Variable: D(GLSRESID)

Method: Least Squares

Date: 12/11/17 Time: 03:44

Sample (adjusted): 1993 2016

Included observations: 24 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GLSRESID(-1)	-1.088908	0.259205	-4.200952	0.0004
D(GLSRESID(-1))	0.344883	0.204331	1.687866	0.1056

R-squared	0.471657	Mean dependent var	-6.061405
Adjusted R-squared	0.447641	S.D. dependent var	1296.951
S.E. of regression	963.9053	Akaike info criterion	16.65952
Sum squared resid	20440496	Schwarz criterion	16.75769
Log likelihood	-197.9142	Hannan-Quinn criter.	16.68556
Durbin-Watson stat	1.968599		

NET_EN_IMP

Null Hypothesis: NET_EN_IMP has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 1 (Automatic - based on SIC, maxlag=6)

		t-Statistic
Elliott-Rothenberg-Stock DF-GLS test statistic		-1.005776
Test critical values:	1% level	-3.770000
	5% level	-3.190000
	10% level	-2.890000

*Elliott-Rothenberg-Stock (1996, Table 1)

Warning: Test critical values calculated for 50 observations

and may not be accurate for a sample size of 25

DF-GLS Test Equation on GLS Detrended Residuals

Dependent Variable: D(GLSRESID)

Method: Least Squares

Date: 12/11/17 Time: 03:45

Sample (adjusted): 1992 2016

Included observations: 25 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GLSRESID(-1)	-0.062263	0.061906	-1.005776	0.3250
D(GLSRESID(-1))	0.552597	0.178572	3.094542	0.0051

R-squared	0.288550	Mean dependent var	0.766051
Adjusted R-squared	0.257617	S.D. dependent var	8.208999
S.E. of regression	7.073009	Akaike info criterion	6.827068
Sum squared resid	1150.632	Schwarz criterion	6.924578
Log likelihood	-83.33834	Hannan-Quinn criter.	6.854113
Durbin-Watson stat	2.346263		

D(Net_EN_IMP)

Null Hypothesis: D(NET_EN_IMP) has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic - based on SIC, maxlag=6)

		t-Statistic
Elliott-Rothenberg-Stock DF-GLS test statistic		-4.574770
Test critical values:	1% level	-3.770000
	5% level	-3.190000
	10% level	-2.890000

*Elliott-Rothenberg-Stock (1996, Table 1)

Warning: Test critical values calculated for 50 observations and may not be accurate for a sample size of 25

DF-GLS Test Equation on GLS Detrended Residuals

Dependent Variable: D(GLSRESID)

Method: Least Squares

Date: 12/11/17 Time: 03:45

Sample (adjusted): 1992 2016

Included observations: 25 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GLSRESID(-1)	-0.967510	0.211488	-4.574770	0.0001

R-squared	0.464794	Mean dependent var	-0.351186
Adjusted R-squared	0.464794	S.D. dependent var	8.187361
S.E. of regression	5.989689	Akaike info criterion	6.457134
Sum squared resid	861.0330	Schwarz criterion	6.505889
Log likelihood	-79.71418	Hannan-Quinn criter.	6.470657
Durbin-Watson stat	1.916890		

POP

Null Hypothesis: POP has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 2 (Automatic - based on SIC, maxlag=6)

		t-Statistic
Elliott-Rothenberg-Stock DF-GLS test statistic		-3.278728
Test critical values:	1% level	-3.770000
	5% level	-3.190000
	10% level	-2.890000

*Elliott-Rothenberg-Stock (1996, Table 1)

Warning: Test critical values calculated for 50 observations

and may not be accurate for a sample size of 24

DF-GLS Test Equation on GLS Detrended Residuals

Dependent Variable: D(GLSRESID)

Method: Least Squares

Date: 12/11/17 Time: 03:37

Sample (adjusted): 1993 2016

Included observations: 24 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GLSRESID(-1)	-0.080683	0.024608	-3.278728	0.0036
D(GLSRESID(-1))	0.178337	0.216498	0.823735	0.4193
D(GLSRESID(-2))	1.306867	0.304550	4.291145	0.0003

R-squared	0.915746	Mean dependent var	-0.000272
Adjusted R-squared	0.907722	S.D. dependent var	0.001275
S.E. of regression	0.000387	Akaike info criterion	-12.75789
Sum squared resid	3.15E-06	Schwarz criterion	-12.61063
Log likelihood	156.0946	Hannan-Quinn criter.	-12.71882
Durbin-Watson stat	1.898165		

POP_ACCESS_PERCENT

Null Hypothesis: POP_AC_SHARE has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic - based on SIC, maxlag=6)

	t-Statistic
Elliott-Rothenberg-Stock DF-GLS test statistic	-7.131401

Test critical values:	1% level	-3.770000
	5% level	-3.190000
	10% level	-2.890000

*Elliott-Rothenberg-Stock (1996, Table 1)

Warning: Test critical values calculated for 50 observations

and may not be accurate for a sample size of 26

DF-GLS Test Equation on GLS Detrended Residuals

Dependent Variable: D(GLSRESID)

Method: Least Squares

Date: 12/19/17 Time: 05:24

Sample (adjusted): 1991 2016

Included observations: 26 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GLSRESID(-1)	-1.340720	0.188002	-7.131401	0.0000

R-squared	0.670430	Mean dependent var	0.007932
Adjusted R-squared	0.670430	S.D. dependent var	3.506612
S.E. of regression	2.013081	Akaike info criterion	4.274913
Sum squared resid	101.3124	Schwarz criterion	4.323301
Log likelihood	-54.57386	Hannan-Quinn criter.	4.288847
Durbin-Watson stat	2.238321		

RE_02

Null Hypothesis: RE_02 has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 3 (Automatic - based on SIC, maxlag=6)

	t-Statistic

Elliott-Rothenberg-Stock DF-GLS test statistic		-1.876586
Test critical values:	1% level	-3.770000
	5% level	-3.190000
	10% level	-2.890000

*Elliott-Rothenberg-Stock (1996, Table 1)

Warning: Test critical values calculated for 50 observations

and may not be accurate for a sample size of 23

DF-GLS Test Equation on GLS Detrended Residuals

Dependent Variable: D(GLSRESID)

Method: Least Squares

Date: 12/11/17 Time: 03:39

Sample (adjusted): 1994 2016

Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GLSRESID(-1)	-0.075628	0.040301	-1.876586	0.0760
D(GLSRESID(-1))	0.241974	0.202634	1.194144	0.2471
D(GLSRESID(-2))	0.503408	0.197752	2.545657	0.0197
D(GLSRESID(-3))	0.442865	0.226593	1.954452	0.0655

R-squared	0.745671	Mean dependent var	0.057293
Adjusted R-squared	0.705513	S.D. dependent var	0.257404
S.E. of regression	0.139684	Akaike info criterion	-0.942094
Sum squared resid	0.370722	Schwarz criterion	-0.744616
Log likelihood	14.83408	Hannan-Quinn criter.	-0.892429
Durbin-Watson stat	2.035788		

D(RE_02)

Null Hypothesis: D(RE_02) has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic - based on SIC, maxlag=6)

		t-Statistic
Elliott-Rothenberg-Stock DF-GLS test statistic		-4.531340
Test critical values:	1% level	-3.770000
	5% level	-3.190000
	10% level	-2.890000

*Elliott-Rothenberg-Stock (1996, Table 1)

Warning: Test critical values calculated for 50 observations

and may not be accurate for a sample size of 25

DF-GLS Test Equation on GLS Detrended Residuals

Dependent Variable: D(GLSRESID)

Method: Least Squares

Date: 12/11/17 Time: 03:40

Sample (adjusted): 1992 2016

Included observations: 25 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GLSRESID(-1)	-0.910753	0.200990	-4.531340	0.0001

R-squared	0.461005	Mean dependent var	-0.001886
Adjusted R-squared	0.461005	S.D. dependent var	0.169163
S.E. of regression	0.124193	Akaike info criterion	-1.294778
Sum squared resid	0.370175	Schwarz criterion	-1.246023
Log likelihood	17.18473	Hannan-Quinn criter.	-1.281256

Durbin-Watson stat	2.067347

UNEMP

Null Hypothesis: UNEMP has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic - based on SIC, maxlag=6)

		t-Statistic
Elliott-Rothenberg-Stock DF-GLS test statistic		-3.712331
Test critical values:	1% level	-3.770000
	5% level	-3.190000
	10% level	-2.890000

*Elliott-Rothenberg-Stock (1996, Table 1)

Warning: Test critical values calculated for 50 observations

and may not be accurate for a sample size of 26

DF-GLS Test Equation on GLS Detrended Residuals

Dependent Variable: D(GLSRESID)

Method: Least Squares

Date: 12/11/17 Time: 03:41

Sample (adjusted): 1991 2016

Included observations: 26 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GLSRESID(-1)	-0.719316	0.193764	-3.712331	0.0010

R-squared	0.355253	Mean dependent var	-0.003825
Adjusted R-squared	0.355253	S.D. dependent var	0.301555
S.E. of regression	0.242137	Akaike info criterion	0.039079

Sum squared resid	1.465762	Schwarz criterion	0.087467
Log likelihood	0.491975	Hannan-Quinn criter.	0.053013
Durbin-Watson stat	2.111038		

RE_TO_FE_TARIFF

Null Hypothesis: RE_TO_FE_TARIFF has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=6)

		t-Statistic
Elliott-Rothenberg-Stock DF-GLS test statistic		-0.845005
Test critical values:	1% level	-2.660720
	5% level	-1.955020
	10% level	-1.609070

*MacKinnon (1996)

DF-GLS Test Equation on GLS Detrended Residuals

Dependent Variable: D(GLSRESID)

Method: Least Squares

Date: 12/11/17 Time: 04:30

Sample (adjusted): 1992 2016

Included observations: 25 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GLSRESID(-1)	-0.032600	0.038580	-0.845005	0.4068
D(GLSRESID(-1))	0.760908	0.158280	4.807348	0.0001

R-squared	0.442498	Mean dependent var	-0.242491
Adjusted R-squared	0.418259	S.D. dependent var	0.637833

S.E. of regression	0.486488	Akaike info criterion	1.473408
Sum squared resid	5.443416	Schwarz criterion	1.570918
Log likelihood	-16.41760	Hannan-Quinn criter.	1.500453
Durbin-Watson stat	2.177161		

D(RE_TO_FE_TARIFF)

Null Hypothesis: D(RE_TO_FE_TARIFF) has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=6)

		t-Statistic
Elliott-Rothenberg-Stock DF-GLS test statistic		-2.180668
Test critical values:	1% level	-2.660720
	5% level	-1.955020
	10% level	-1.609070

*MacKinnon (1996)

DF-GLS Test Equation on GLS Detrended Residuals

Dependent Variable: D(GLSRESID)

Method: Least Squares

Date: 12/11/17 Time: 04:35

Sample (adjusted): 1992 2016

Included observations: 25 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GLSRESID(-1)	-0.327630	0.150243	-2.180668	0.0392

R-squared	0.165008	Mean dependent var	-0.010700
Adjusted R-squared	0.165008	S.D. dependent var	0.523162

S.E. of regression	0.478055	Akaike info criterion	1.400995
Sum squared resid	5.484871	Schwarz criterion	1.449750
Log likelihood	-16.51244	Hannan-Quinn criter.	1.414517
Durbin-Watson stat	2.038684		

Appendix D: Pair-wise Granger causality tests

Granger causality test shows the direction of causality. Granger causality between two time-series variables x_t and y_t can be defined in terms of error prediction as

$$if\ \sigma^2(x \perp \bar{u}) < \sigma^2(x \perp \overline{u-y}), \qquad (D1)$$

then, $y \rightarrow x$, i.e. y is causing x, where, $\bar{u}$ represents information set on past of x and y.

$(\overline{u-y})$ is the information set excluding the information on y.

Equation (D1) represents the error prediction of x that can be better explained by taking past of x as well as past of y than taking part of x only.

Similarly, if $\sigma^2(x \perp \bar{u}) < \sigma^2(x \perp \overline{u-y})$ and $\sigma^2(y \perp \bar{u}) < \sigma^2(x \perp \overline{u-x})$, then it is said that the causal relationship is a feedback relationship.

Pairwise Granger Causality Tests

Date: 12/11/17 Time: 04:10

Sample: 1990 2016

Lags: 5

Null Hypothesis:	Obs	F-Statistic	Prob.
CALL_RATE does not Granger Cause D_RE_02	21	1.13861	0.4011
D_RE_02 does not Granger Cause CALL_RATE		2.66604	0.0878

Pairwise Granger Causality Tests

Date: 12/10/17 Time: 20:48

Sample: 1990 2016

Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
D_FIS_DEF does not Granger Cause D_RE_02	24	6.50319	0.0071
D_RE_02 does not Granger Cause D_FIS_DEF		0.69591	0.5109

Pairwise Granger Causality Tests

Date: 12/10/17 Time: 20:48

Sample: 1990 2016

Lags: 3

Null Hypothesis:	Obs	F-Statistic	Prob.
D_FIS_DEF does not Granger Cause D_RE_02	23	3.40231	0.0435
D_RE_02 does not Granger Cause D_FIS_DEF		1.82745	0.1828

Pairwise Granger Causality Tests

Date: 12/10/17 Time: 20:48

Sample: 1990 2016

Lags: 5

Null Hypothesis:	Obs	F-Statistic	Prob.
D_FIS_DEF does not Granger Cause D_RE_02	21	1.36122	0.3164
D_RE_02 does not Granger Cause D_FIS_DEF		21.5986	5.E-05

Pairwise Granger Causality Tests

Date: 12/10/17 Time: 20:49

Sample: 1990 2016

Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
D_GDP_CONS_01 does not Granger Cause D_RE_02	24	16.6956	7.E-05
D_RE_02 does not Granger Cause D_GDP_CONS_01		2.39273	0.1184

Pairwise Granger Causality Tests

Date: 12/10/17 Time: 20:49

Sample: 1990 2016

Lags: 3

Null Hypothesis:	Obs	F-Statistic	Prob.
D_GDP_CONS_01 does not Granger Cause D_RE_02	23	14.1944	9.E-05
D_RE_02 does not Granger Cause D_GDP_CONS_01		1.89111	0.1718

Pairwise Granger Causality Tests

Date: 12/10/17 Time: 20:49

Sample: 1990 2016

Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
D_GDP_CONS_01 does not Granger Cause D_RE_02	22	9.50823	0.0008
D_RE_02 does not Granger Cause D_GDP_CONS_01		0.97230	0.4556

Pairwise Granger Causality Tests

Date: 12/10/17 Time: 20:50

Sample: 1990 2016

Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
D_NET_EN_IMP does not Granger Cause D_RE_02	24	0.78734	0.4693
D_RE_02 does not Granger Cause D_NET_EN_IMP		8.89025	0.0019

Pairwise Granger Causality Tests

Date: 12/10/17 Time: 20:51

Sample: 1990 2016

Lags: 3

Null Hypothesis:	Obs	F-Statistic	Prob.
D_NET_EN_IMP does not Granger Cause D_RE_02	23	1.24133	0.3276
D_RE_02 does not Granger Cause D_NET_EN_IMP		9.40820	0.0008

Pairwise Granger Causality Tests

Date: 12/10/17 Time: 20:51

Sample: 1990 2016

Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
D_NET_EN_IMP does not Granger Cause D_RE_02	22	1.38964	0.2914
D_RE_02 does not Granger Cause D_NET_EN_IMP		13.8777	0.0001

Pairwise Granger Causality Tests

Date: 12/10/17 Time: 20:52

Sample: 1990 2016

Lags: 5

Null Hypothesis:	Obs	F-Statistic	Prob.
D_RE_TO_FE_TARIFF does not Granger Cause D_RE_02	21	3.13806	0.0584
D_RE_02 does not Granger Cause D_RE_TO_FE_TARIFF		0.94410	0.4936

Pairwise Granger Causality Tests

Date: 12/10/17 Time: 20:52

Sample: 1990 2016

Lags: 6

Null Hypothesis:	Obs	F-Statistic	Prob.
D_RE_TO_FE_TARIFF does not Granger Cause D_RE_02	20	9.72347	0.0042
D_RE_02 does not Granger Cause D_RE_TO_FE_TARIFF		0.85800	0.5660

Pairwise Granger Causality Tests

Date: 12/10/17 Time: 20:52

Sample: 1990 2016

Lags: 7

Null Hypothesis:	Obs	F-Statistic	Prob.
D_RE_TO_FE_TARIFF does not Granger Cause D_RE_02	19	21.6109	0.0050
D_RE_02 does not Granger Cause D_RE_TO_FE_TARIFF		7.04383	0.0390

Pairwise Granger Causality Tests

Date: 12/10/17 Time: 20:56

Sample: 1990 2016

Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
POP does not Granger Cause D_RE_02	24	5.74926	0.0112
D_RE_02 does not Granger Cause POP		0.49912	0.6148

Pairwise Granger Causality Tests

Date: 12/10/17 Time: 20:56

Sample: 1990 2016

Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
POP does not Granger Cause D_RE_02	22	2.21538	0.1239
D_RE_02 does not Granger Cause POP		5.69944	0.0071

Pairwise Granger Causality Tests

Date: 12/10/17 Time: 20:56

Sample: 1990 2016

Lags: 3

Null Hypothesis:	Obs	F-Statistic	Prob.
POP does not Granger Cause D_RE_02	23	3.12644	0.0551
D_RE_02 does not Granger Cause POP		2.80830	0.0730

Pairwise Granger Causality Tests

Date: 12/19/17 Time: 05:30

Sample: 1990 2016

Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
POP_AC_SHARE does not Granger Cause RE_02	25	7.41283	0.0039
RE_02 does not Granger Cause POP_AC_SHARE		5.14909	0.0157

Pairwise Granger Causality Tests

Date: 12/19/17 Time: 05:32

Sample: 1990 2016

Lags: 3

Null Hypothesis:	Obs	F-Statistic	Prob.
POP_AC_SHARE does not Granger Cause RE_02	24	5.62099	0.0073
RE_02 does not Granger Cause POP_AC_SHARE		1.30246	0.3060

Pairwise Granger Causality Tests

Date: 12/19/17 Time: 05:32

Sample: 1990 2016

Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
POP_AC_SHARE does not Granger Cause RE_02	23	3.02579	0.0542
RE_02 does not Granger Cause POP_AC_SHARE		2.54232	0.0863

Pairwise Granger Causality Tests

Date: 12/11/17 Time: 04:18

Sample: 1990 2016

Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
UNEMP does not Granger Cause D_RE_02	24	0.53943	0.5918
D_RE_02 does not Granger Cause UNEMP		3.12879	0.0669

Pairwise Granger Causality Tests

Date: 12/11/17 Time: 04:19

Sample: 1990 2016

Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.

UNEMP does not Granger Cause D_RE_02	22	0.21882	0.9232
D_RE_02 does not Granger Cause UNEMP		2.65757	0.0807

Pairwise Granger Causality Tests

Date: 12/11/17 Time: 04:19

Sample: 1990 2016

Lags: 5

Null Hypothesis:	Obs	F-Statistic	Prob.
UNEMP does not Granger Cause D_RE_02	21	0.31384	0.8936
D_RE_02 does not Granger Cause UNEMP		2.65193	0.0889

Pairwise Granger Causality Tests

Date: 12/11/17 Time: 04:19

Sample: 1990 2016

Lags: 6

Null Hypothesis:	Obs	F-Statistic	Prob.
UNEMP does not Granger Cause D_RE_02	20	0.41966	0.8450
D_RE_02 does not Granger Cause UNEMP		4.36970	0.0372

Appendix E: ARDL model with co-integration, long-run coefficient estimation and bound tests

Once the order of integration of a time series is decided, based on the unit-root tests, it is essential to check whether there is any long-run equilibrium co-integrating relation among the variables or not. That is, do the variables display co-movement over extended periods of time.

There are different methodologies to check the long-run co-integrating relation, such as Engel-Granger co-integration test, Johansen co-integration test, Auto-regressive distributed lag (ARDL) co-integration test, etc. Among these tests, Engel-Granger co-integration test is applicable only for a bi-variate model, which is not the case here. In fact, to determine the long-run and short-run relationships among variables, the traditionally prescribed approach is the standard Johansen co-integration and vector error-correction model (VECM); but, this methodology suffers from several serious flaws as shown by Pesaran et al. (2001). Johansen co-integration tests can find the long-run relationship among variables if all the variables are I(1) only, that is, they are integrated of order one. ARDL co-integration model has the advantage in comparison with the Engel-Granger co-integration test and as well as Johansen co-integration test in that ARDL approach can be applied to find the long-run relationship between variables irrespective of whether the underlying variables are purely I(0), purely I(1), or a mix of both. In fact, this is the case for the variables being considered by in analysis. This superiority of ARDL estimation over Johansen co-integration and Engel-Granger co-integration tests has motivated us to use ARDL methodology for our analysis.

A standard ARDL model (with four variables (X, Y, Z and K) with long-run co-integrating relationship can be represented as follows:

$$DX_t = \alpha + \beta_1 X_{t-1} + \beta_2 Y_{t-1} + \beta_3 Z_{t-1} + \beta_4 K_{t-1} + \sum_{i=1}^{P} \delta_{1i} DX_{t-i}$$

$$+ \sum_{i=0}^{P} \delta_{2i} DY_{t-i} + \sum_{i=0}^{P} \delta_{3i} DZ_{t-i} + \sum_{i=0}^{P} \delta_{4i} DK_{t-i} + \varepsilon_t \qquad (E1)$$

where D denotes the first difference operator, α is the drift component, ε_t is the usual white noise residuals and the maximum number of lags "P" is selected using Akaike Information Criterion (AIC).

Here, in equation (E1), β_1, β_2, β_3 and β_4 represent the long-run coefficients of relationship among the variables (in our result β_1 is normalized to 1). Finally, to check whether there is any stable equilibrium long-run co-integrating relation among the four variables X, Y, Z and K, the null hypothesis of the non-existence of a long-run relationship is tested H_0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$, against the alternative hypothesis that there is a long-run relationship among the four variables X, Y, Z and K, i.e., H_A: $\beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq 0$.

While checking for the long-run relationship, the bound test is used for an ARDL kind of framework. The bound test deals with the null hypothesis of non-existence of a long-run relationship, and it is tested for H_0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ against the alternative hypothesis that there is a long-run relationship among the four variables X, Y, Z and K, i.e., H_A: $\beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq 0$. If the calculated F-statistics, which indicates the overall significance is less than both the upper bound critical value as well as the lower bound critical value, then it says that the null hypothesis of the non-existence of any long-run relationship is accepted. On the other hand, if the calculated F-statistics is greater than both the lower bound critical value and as well as the upper bound critical value, then the null hypothesis that there is no long-run relationship among the variables is rejected.

The detailed results obtained are listed below, and discussed in the main text of the report.

ARDL Cointegrating And Long Run Form

Original dep. variable: RE_02

Selected Model: ARDL(1, 0, 1, 1, 1, 1, 0, 1, 0)

Date: 12/19/17 Time: 05:18

Sample: 1990 2016

Included observations: 26

Cointegrating Form

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CALL_RATE	0.000647	0.004940	0.131013	0.8981
D(FIS_DEF)	0.000042	0.000032	1.283336	0.2258
D(GDP_CONS_01)	-0.000003	0.000018	-0.174965	0.8643
D(NET_EN_IMP)	0.006476	0.002868	2.257873	0.0453
D(POP)	-43.251861	14.166481	-3.053113	0.0110
POP_AC_SHARE	0.000986	0.003912	0.251979	0.8057
D(UNEMP)	-0.128873	0.054576	-2.361324	0.0377
RE_TO_FE_TARIFF	-0.003348	0.012251	-0.273253	0.7897
CointEq(-1)	-0.462002	0.080791	-5.718472	0.0001

Cointeq = RE_02 - (0.0017*CALL_RATE -0.0000*FIS_DEF + 0.0001
*GDP_CONS_01 -0.0017*NET_EN_IMP -11.6036*POP -0.0055
*POP_ACCESS_PERCENT -0.1475*UNEMP + 0.0594*RE_TO_FE_TARIFF
+ 9.2186)

Long Run Coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CALL_RATE	0.001748	0.015411	0.113445	0.9117
FIS_DEF	-0.000036	0.000111	-0.325161	0.7512
GDP_CONS_01	0.000135	0.000051	2.665089	0.0220
NET_EN_IMP	-0.001669	0.013684	-0.121932	0.9052
POP	-11.603577	2.610317	-4.445275	0.0010
POP_AC_SHARE	-0.005474	0.028352	-0.193082	0.8504
UNEMP	-0.147545	0.328919	-0.448575	0.6624
RE_TO_FE_TARIFF	0.059370	0.052002	1.141706	0.2778
C	9.218636	2.322618	3.969071	0.0022

ARDL Bounds Test

Date: 12/19/17 Time: 05:21

Sample: 1991 2016

Included observations: 26

Null Hypothesis: No long-run relationships exist

Test Statistic	Value	k
F-statistic	5.477802	8

Critical Value Bounds

Significance	I0 Bound	I1 Bound
10%	1.85	2.85
5%	2.11	3.15
2.5%	2.33	3.42
1%	2.62	3.77

Appendix F: Detailed methodology for calculating ESI

Methodology

We employ the distance based methodology (Sarma, 2012) in order to compute a comprehensive index measuring energy security. Suppose, we have p dimensions which capture energy security, each denoted by $X_{i\_n}; i = 1(1)p$ (where p is a finite integer), a normalized ESI could be expressed as a mapping from p-dimensional real space to 1 dimensional real space. That is,

$$ESI: \mathbb{R}_{+}^{p} \to \mathbb{R}_{+}^{1},$$

where

$$ESI = g(X_{1\_n}, X_{2\_n}, \dots, X_{p\_n}); g'(X_{i\_n}) > 0 \; \& \; ESI \in [0, 1]. \qquad (F1)$$

Steps

1. If for any dimension, its value is not unit free and not bounded between zero and one, then we normalize each of these in such a manner that they are bounded, unit free and monotone. Suppose the original series is given by X_i, then

   $$X_{i\_n} = \frac{X_i - m_i}{M_i - m_i}, \qquad (F2)$$

   where

   $m_i$is the minimum value of indicator i;

   $M_i$is the maximum value of indicator i.

   (E2) gives us the dimension index for each dimension. X_{i_n} denotes the achievement in the i^{th} dimension, i.e., $X \equiv X(X_{1_n}, X_{2_n}, \dots, X_{p_n})$. A higher value of X_{i_n} indicates a higher level of achievement in terms of dimension i. Unlike Sarma (2012), we use identical weights for each of the dimensions, i.e., unity. That is, all dimensions are considered equally important. The drawback of this methodology is that the weights are arbitrarily chosen. By choosing an alternative vector of weights, a different set of estimates of ESI will be derived.
2. In a p-dimensional space, the point $O(0, 0, \dots., 0)$ indicates the worst situation (or point) while the point $I(1, 1, \dots., 1)$ indicates the highest achievement point (bliss point) for each of the indicators. A larger distance between X and O indicates higher energy security, whereas a smaller distance between I and X denotes higher energy security.
3. It is not unlikely that achievement points for two or more years are at the same distance from I but at different distances from O. In that case, the achievement point, whose distance from O is greater would ensure a better situation in terms of energy security.
4. The ESI for year t; $(t = 1(1)T)$ is given by the simple average of the normalized Euclidean distance between O and X_{i_n} for the year t and normalised inverse Euclidean distance between X_{i_n} for the year t and I.

$$ESI = \frac{X+(1-Y)}{2}, \qquad (F3)$$

where

$$X = \frac{\sqrt{\sum_{i=1}^{p} X_{i\_n}^{2}}}{\sqrt{\sum_{i=1}^{p} 1^{2}}} \qquad (F4)$$

and

$$Y = \frac{\sqrt{\sum_{i=1}^{p} \left(1-X_{i\_n}\right)^{2}}}{\sqrt{\sum_{i=1}^{p} 1^{2}}}. \qquad (F5)$$

In (F4) and (F5), we calculate the Euclidian distance between O and X, and X and I respectively. Both these distances are normalized by the distance between O and I in order that they lie between 0 and 1. Furthermore, in (F3), the inverse distance between X and I is considered. This ensures that a higher distance implies higher energy security.