Using real options to study the impact of capacity additions and investment expenditures in renewable energies in India

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Abstract

We calculate the overall policy value of installed capacity additions and investment expenditures in wind and solar energies in India. Recent increases in capacity additions and investments by both the public and private sectors alongwith government support schemes have made these energies more competitive with traditional fuels like coal in generating electricity. We use a two-factor learning curve to model the decline in prices of wind and solar energies. Employing a real options approach with global coal prices as the stochastic variable we find the overall value of promotion policies in renewables to be sufficiently large. Reducing the share of coal in electricity generation is one of India's stated goals and a high trigger price of coal suggests continued efforts of capacity additions and investment expenditures in the solar and wind sectors are needed for some time in India.

Keywords: India Electricity, Wind and Solar, Installed Capacities, Investment Expenditures, Real Options
JEL codes: C61, C63, L94, Q42, Q43, Q48

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1 Introduction

India's Electricity Act of 2003 (the Act) came with provisions for introducing competition in the power sector, protect consumer's interests and provide power for all citizens.[1] The Act which was further amended by the Electricity (Amendment) Act of 2007 had an important feature of the mandatory establishment of State Electricity Regulatory Commissions (SERCs) and the unbundling of the process of generation, transmission and distribution of electricity ((Ministry of Power, 2018)). This allowed renewable energy based electricity generation companies sell power to transmission and distribution utilities within a state and in turn permit the distribution companies to meet their renewable purchase obligations.[2] Section 63 of the Act also permits a state to select renewable energy producers through tariff-based competitive bidding which is intended to reduce the price of electricity faced by consumers. This price for distribution and supply of electricity within a state is determined under the aegis of the respective SERCs.[3] Overall, there has been a steady decline in wind and solar tariffs in India and (Buckley and Sharda, 2015) estimate the solar levelized cost of electricity (LCOE) in India to have fallen to Rs. 6.17/Kilowatt-hour (KWh) (US $ 9.71c/KWh) from previous levels of Rs. 6.49/KWh (US $ 10.21c/KWh). There were bids of solar tariffs as low as Rs. 2.44/KWh (US $ 3.84c/KWh) at the auction of 500 MW capacity in the Bhadla Solar Park in Rajasthan ((Economic Times, 2018a)). For wind, (International Renewable Energy Agency (IRENA), 2015) estimate levelized costs for large-scale projects to have fallen to US $ 8c/KWh and depending on power purchase agreements signed between the generator and offtaker such as a distribution utility, (CRISIL Ratings, 2018) estimate wind tariffs to be around Rs. 3/KWh (US $ 4.72c/KWh) until 2019. (Bridge to India, 2017) finds 88% of investments in solar capacity is in form of utility-scale solar projects

[1] India, with a population of 1.27 billion had about 260 million or 21.3% of the population without access to electricity until 2015 ((The World Bank, 2017)).

[2] The renewable purchase obligation targets were set to 8% for solar energy by 2019 and 15% for wind energy by 2020 by the Government of India ((Buckley and Sharda, 2015)).

[3] (Qiu and Anadon, 2012) discuss competitive bidding for developing wind farms during the expansion of China's wind energy industry from 2003 to 2007.

undertaken by public and private investors, including domestic and international project developers. The entry of large foreign project developers in both the solar and wind energy sectors in India has led to many joint ventures with various state governments in India (see (Buckley and Sharda, 2015)) and the project developers have also been awarded power purchase agreements due to their competitive bids.

The fall in solar and wind tariffs in India can be attributed to capacity additions and investment expenditures in renewable energies and government support schemes for wind and solar. Some of these include the central (national) government offering subsidy up to 30% of the system cost for solar rooftops for industrial and residential consumers and accelerated depreciation benefits up to 80% of depreciation in the first year of installation of the project and excise duty exemption and concession on import duties on components and equipment required to set up large wind and solar power projects ((Government of Karnataka, 2010), (Government of Andhra Pradesh, 2015a), (Bridge to India, 2016)). The Jawaharlal Nehru National Solar Mission (JNNSM) was launched by the Government of India in 2010 with an objective to make India a leader in solar power and an amount of Rs. 150.5 billion (US $ 2.37 billion) was put forward by the central government as the total support for all additions to solar capacities and rooftop solar in the first phase of installation of the JNNSM up to 2012-13 with a target of about 20 gigawatts (GW) ((Government of India, 2011), (Government of India, 2016)). New investments in renewable energies in India increased on average by 11% over 2004-17 and in 2017, developing countries invested US $ 177 billion in renewables which was more compared to that of US $ 103 billion by developed ones ((Bloomberg New Energy Finance, 2018)).[4] We find investments in solar and wind energy sectors in India for 2017 totaled US $ 6.7 and 4 billion and US $ 5.5 and 3.8 billion for 2016 respectively. Furthermore, government and corporate research and development (R&D) investments for 2016 stood at US $ 10 million and 0.4 million respectively ((Bloomberg New

[4] Highest renewable energy investments for 2017 was China accounting for US $ 126.6 billion or 45% of the world total.

Energy Finance, 2017), (Bloomberg New Energy Finance, 2018)). Figure (1) shows India's capacity additions in renewable energies over recent years.[5] The installed generating capac-

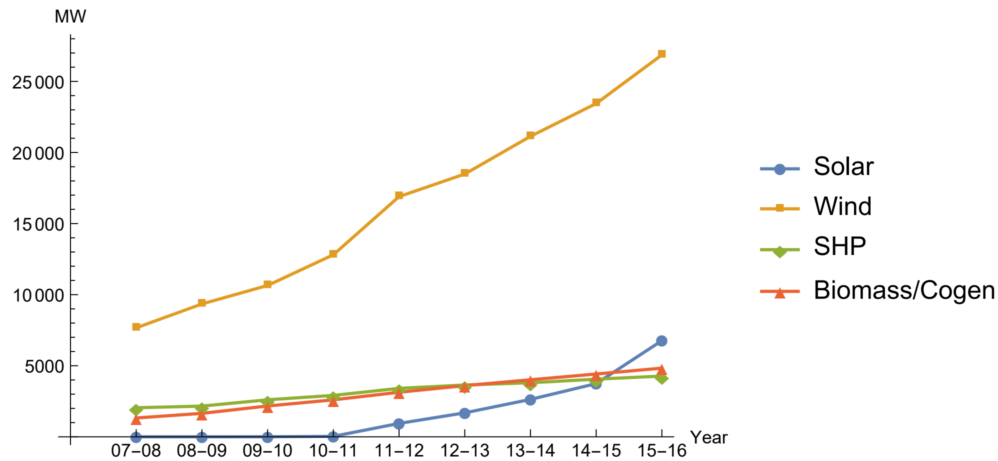


Figure 1: Installed Capacities of Selected Renewable Energy Sources (RES)

ity for solar increased from 2.12 MW in 2007-08 to 32.39 MW in 2010-11 to 6762.85 MW in 2015-16 while capacity for wind has grown steadily to reach 26.8 GW for 2015-16. The average growth in capacity addition over the years 2011-12 to 2014-15 for solar was 45.13% while that for wind was 10.9%. The installed capacities for SHP (small hydro power $\leq$ 25 MW) and biomass/cogeneration were 4.3 GW and 4.8 GW respectively in 2015-16. Given that majority of investment expenditures and cumulative capacity additions in renewable energies are directed towards wind and solar, we concentrate on these energies for the rest of our analysis.

2 Related Literature

In this work, we propose a real options model to study the value of promotion policies of investment expenditures and additions to installed capacities for wind and solar energies in India. We evaluate a model where a greater use of wind and solar in electricity generation helps India to achieve its domestic targets and Paris Agreement goals as stated in Intended

[5] India's fiscal year ranges from April 1-March 31.

Nationally Determined Contribution (INDC) targets submitted to the UN framework convention on climate change. Specifically, the domestic target includes installing capacities of 100 GW of solar, 60 GW of wind and 15 GW from other sources such as small hydro power, biomass and urban and industrial waste by 2021-22 and reducing emission per unit of GDP by 33-35% from 2005 levels and to produce 40% of electricity from non-fossil fuel sources by the year 2030 as part of its Paris targets.[6] Wind and solar energies can be especially important in light of India's growing electricity demand due to growth in population, urbanization, transport demand and industrial production which would need an even greater dependence on coal. India has traditionally relied on coal to generate the bulk of its electricity and the share of coal in electricity generation has been about three-quarters in recent years ((Central Statistics Office, 2015), (Central Statistics Office, 2016)). Moreover, in view of a rising coal import bill and pollution concerns, promotion of renewable energies through decentralized and distributed generation and setting up microgrids on top of mobile phone towers particularly for remote areas without access to the electricity grid and/or unstable supply due to transmission and distribution losses is relevant for India having more than 10 million circuit kms of tranmission lines ((Buckley and Sharda, 2015)). (Chakravorty et al., 2014) empirically analyze the effect of improved access of electricity for rural Indian households and conclude that connecting a rural household to the electricity grid (and with fewer power outages) has a big positive impact on household income.[7]

Real options considers the flexibility of the management or decision maker to make an irreversible investment in a project depending on the arrival of future information ((Dixit and Pindyck, 1994)). The option pricing theory of finance proposed by (Black and Scholes, 1973) and (Merton, 1973) was used by (Myers, 1977) in context of real assets who stated that profits

[6] The Paris Agreement targets for India also constitute creating an additional carbon sink of 2.5 billion tonnes of CO_2 equivalent through extra forest and tree cover by 2030.

[7] India has one of the highest aggregate technical and commercial losses (transmission and distribution losses and the additional energy that is lost because of theft and defective metering and errors in estimating unmetered supplies) in the world ((Central Statistics Office, 2015), (Dubey et al., 2014)). Small distributed capacity investment for solar PV projects ≤ 1 MW in India has been constant at about US \$ 1 billion over 2016 and 2017 ((Bloomberg New Energy Finance, 2017), (Bloomberg New Energy Finance, 2018)).

created by cash flow generated from an investment arise from the use of currently owned assets and the option of cash flows from future investment opportunities. Applications of real options can be found in investments in wind energy and hydropower ((Venetsanos et al., 2002), (Kjrland, 2007)) and valuing oil properties and offshore petroleum leases in (Paddock et al., 1988). Real options therory rests on the situation that if a decision maker (or a social planner in our context) has 'x' years to make an investment in a project incurring a sunk cost I, investing now or in the future depends on arrival of future information: we can wait to invest until market conditions (prices, demand) improve. This additional value of waiting gives the project a higher value than evaluating with a traditional Net Present Value (NPV) approach where cash flows are discounted each period and the investment should be carried out only when NPV> 0, otherwise not. The project value or options value arising from the added managerial flexibility in investment decisions using real options models has been called "Expanded" or "Strategic" NPV by (Trigeorgis, 1993). Since the nature of future information is uncertain, investment under a real options framework should be undertaken when the value of waiting is zero.[8] Here we calculate the benefit of investments in wind and solar energies using global coal prices as the stochastic variable. In context of a policy benefit evaluation model ((Siddiqui et al., 2007) and (Lee and Shih, 2010)), we model the falling prices of wind and solar as a two-factor model ((Klaassen et al., 2005), (Rubin et al., 2015)) where cumulative research expenditures and cumulative installed capacity additions in these sectors are the drivers for cost reduction. We include energy investments in form of venture capital and private equity investments, public and private R&D expenditures and small distributed capacity investments in renewable energies in India.[9] The first contribution of the work lies in finding the value of policies of additions to capacities and research expenditures for solar and wind technologies in India; secondly, comparing the value of deploying additional wind and solar with that of continuing with research expenditures and capacity additions

[8]However, in the absence of uncertainty and faced with a "now or never" decision to invest, traditional NPV analysis gives the correct result.

[9]We include the sum of these investments as data for R&D expenditures are not available for all individual years.

to bring down their costs at each period, we also find the 'trigger price' where the value of waiting is zero. The social planner should exercise the option of deployment of renewable energies at the trigger price of coal. Trigger prices for every time period where the solution changes from continuation to deployment gives interesting results. (Detert and Kotani, 2013) find trigger prices for the case of Mongolia for making the investment for switching to renewables in electricity generation assuming stochastic coal prices. We view this as the second contribution of the paper as related works in the literature do not solve for the trigger price when finding overall policy values of investment programs for renewables.

We clarify the problem of the social planner to invest in 'additional' wind and solar energies as the following. Our calculations show the share of wind and solar in electricity generation to increase from around 5% in 2014-15 to a little above 12% in 2030 and that of coal to drop to about 58%; we assume the shares of hydro and nuclear combined and that of natural gas to remain constant at about 15% and 3% respectively.[10] This implies that for India to meet its Paris targets, the share of wind and solar would have to increase to about 25% and we solve this problem in the context of their falling tariffs and stochastic global coal prices using real options analysis. An an example, the state government of Karnataka announced in 2010 the planned addition of 6600 MW of renewable energy capacities so as to increase the current share of renewables from 11.5% to 20% in total electricity generation by 2015 ((Government of Karnataka, 2010)).

The paper is organized as follows. We proceed with the model and framework and then with the main results. We then move on to discussions and ideas for future research. The final section concludes.

[10] Although technically a fossil fuel, natural gas is the least polluting of all fossil fuel sources ((Hach and Spinler, 2016)). Given capacity addition for nuclear and electricity generated from that sector has been very negligible over recent years, we expect the small but constant share of gas in total electricity generated to be important ((Central Electricity Authority, 2015)), ((Central Electricity Authority, 2017)).

Table 1: Coal Price (US $) Summary Statistics and Dickey Fuller Test

Obs.	145
Mean	51.59
Std. Dev.	29.44
Min	24.45
Max	174.43
Augmented Dickey Fuller Test Results	
t-statistic†	-1.3493
p-value	0.6086

† Critical Values: 1% level = -3.5482; 5% level= -2.9126; 10% level= -2.594

3 Model

3.1 Stochastic Coal Prices

The stochastic variable in our model is international coal prices. (Bastian-Pinto et al., 2009) state that the applicability of different stochastic processes to a particular type of problem is a complicated issue. Proceeding with an augmented Dickey Fuller test to test whether an unit root exists, while we may not be able to reject the null hypothesis of existence of a unit root implying support for a Geometric Brownian Motion (GBM), for a short duration time series, this does not necessarily rule out the possibility of mean reversion or Geometric Mean Reversion (GMR). We use Quarterly data from 1980 to 2016 ((Federal Reserve Bank of St. Louis, 2016)) for global price of coal per ton and since investment decisions in this case can only be made at interval of a quarter and not in any moment, a discrete time model is reasonable ((Boyarchenko and Levendorskii, 2007)). However, in context of India, we use yearly estimates of the parameters of the model since we assume investment decisions in additional energy capacity can only be made for every fiscal year. Data on investment expenditures in clean energy in India are also available on a yearly basis ((Bloomberg New Energy Finance, 2017), (Bloomberg New Energy Finance, 2018)). Summary statistics of the data and results of the augmented Dickey Fuller test are presented in table (1). Results from table (1) imply that the null hypothesis of a unit root cannot be rejected at significance levels of 10%, 5% or 1% and thus coal prices can be modeled as a GBM. However, we would also model global coal prices to follow a GMR since (Dixit and Pindyck, 1994) state that while prices of raw commodities such as coal may fluctuate randomly in the short run, they are related to long term marginal production costs and would thus revert to a long term average.

Coal prices following a stochastic price process of a GBM can be shown as

$$dP_c = \alpha P_c dt + \sigma P_c dz \tag{1}$$

where P_c is the global price of coal, α and σ are constants depicting the rates of drift and variance and dz is a standard Wiener process defined as

$$dz = \epsilon_t \sqrt{dt} \tag{2}$$

where $\epsilon_t \sim N(0,1)$. We approximate the above process by using a binomial lattice such that the change in price through an upward movement is given by $u = e^{\sigma\sqrt{\Delta t}}$, change in price through a downward movement as $d = 1/u$, and the probabilities of an upward and downward movement by $p = \frac{e^{\alpha\Delta t}-d}{u-d}$ and $1-p$ respectively ((Hull, 2012)).[11] We demonstrate sample binomial trees for equations (1) and (7) in figures (2) and (3). The discretized version for the GBM process given by equation (1) can be obtained by setting $dt \approx \Delta t = 1$ and $dP_c \approx P_{c,t+1} - P_{c,t}$

$$P_{c,t+1} = P_{c,t} + \alpha P_{c,t} + \sigma P_{c,t}\epsilon_t \tag{3}$$

Using Ito's Lemma, we know if coal prices follow GBM, then $F(P_c) = lnP_c$ follows a simple Brownian motion as

$$dF = \left(\alpha - \frac{1}{2}\sigma^2\right) dt + \sigma dz \tag{4}$$

[11] Approximating the continuous process given in equation (1) with a binomial lattice in steps of Δt implies discretizing the process. Since investment decisions can be made for every year, we assume $\Delta t = 1$ in our case.

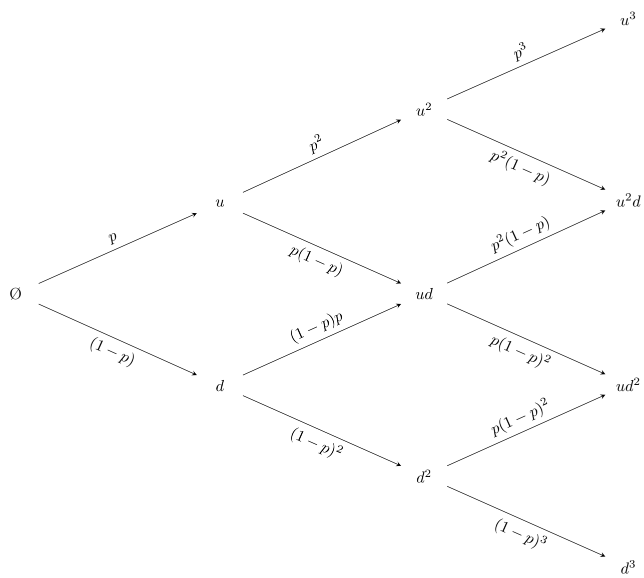


Figure 2: Binomial tree for GBM with 3 periods

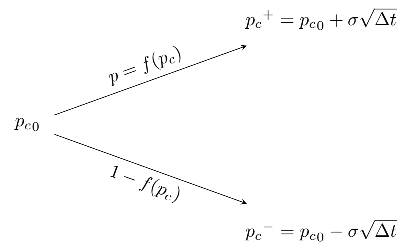


Figure 3: Binomial tree for simple mean reversion

or writing $ln(P_c) = p_c$ we get in discrete time

$$p_{c,t+1} - p_{c,t} = \left(\alpha - \frac{1}{2}\sigma^2\right)\Delta t + \sigma\epsilon_t\sqrt{\Delta t} \tag{5}$$

We use the maximum-likelihood estimates of α and σ. We will have $\alpha = \mu + \left(\frac{1}{2}\right)s^2$ and $\sigma = s$ where μ and s are the mean and the standard deviation respectively of $p_{c,t} - p_{c,t-1}$. For our data, this gives yearly estimates $\alpha = 0.02958$ and $\sigma = 0.20568$.

If coal prices follow the stochastic price process of a GMR we have

$$dP_c = \eta(\bar{P}_c - P_c)P_c dt + \sigma P_c dz \tag{6}$$

where η is the speed of mean reversion, $\bar{P}_c$ is the long term mean to which P_c reverts, σ is the rate of variance and dz is defined by equation (2) as before. To be able to work with a binomial lattice, we transform the above process to a simple mean reversion as ((Nelson and

Ramaswamy, 1990), (Bastian-Pinto et al., 2009))

$$dp_c = \eta(\bar{p_c} - p_c)dt + \sigma dz \tag{7}$$

where $p_c = ln(P_c)$ and $\bar{p_c}$ is the long term mean to which p_c reverts. We use the log of price since it is commonly assumed that commodity prices are lognormally distributed and given $p_c = ln(P_c)$, P_c cannot be negative. Following (Nelson and Ramaswamy, 1990) and (Bastian-Pinto et al., 2010) to construct a recombining binomial tree for the process in equation (7) given initial price p_{c0}, we have for the upward movement ${p_c}^+$, downward movement ${p_c}^-$, up probability p as

$$\begin{aligned} {p_c}^+ &= p_c + \sigma\sqrt{\Delta t} \\ {p_c}^- &= p_c - \sigma\sqrt{\Delta t} \\ p &= \tfrac{1}{2} + \tfrac{\eta(\bar{p_c} - p_c)}{2\sigma}\sqrt{\Delta t} \end{aligned} \tag{8}$$

such that the probability of a downward movement is given by $1 - p$ as before. However, it is clear from equation (8) that probability p can take values less than zero or greater than 1 under certain conditions. This is resolved by censoring the probabilities in the following manner

$$p = \begin{cases} \frac{1}{2} + \frac{\eta(\bar{p_c} - p_c)}{2\sigma}\sqrt{\Delta t}, & \text{if } 0 \leq p \leq 1 \\ 0, & \text{if } p < 0 \\ 1, & \text{otherwise.} \end{cases} \tag{9}$$

For a recombinant binomial tree of simple mean reversion process in equation (7), the probability of an upward movement depends on the current value p_c at that node. Moreover, since successive values are obtained either by adding or subtracting the variance from the previous node, which leads some nodes being very close to each other for smaller numbers (see (Bastian-Pinto et al., 2009), (Bastian-Pinto et al., 2010)), the binomial tree would not be as equally spaced as in figure (2) for a GBM process. Finally, the binomial recombinant tree for the GMR process in equation (6) can be obtained by taking $P_c = exp(p_c)$ at each

Table 2: Geometric Mean Reversion-yearly estimates

Variable	Coefficient	t-statistic†	p-value
a	0.0238	1.386	0.1681
b	-0.00032	-1.106	0.2706
S.E of regression	0.1022		
$\bar{P}_c$	74.378		
η	0.00032		
σ	0.2044		

† Critical Values: 1% level = -3.5482; 5% level= -2.9126; 10% level= -2.594

node. We need to write equation (6) in discrete time following equation (3) to be able to estimate the parameters η, σ and $\bar{P}_c$. Setting $dt \approx \Delta t = 1$ and following (Dixit and Pindyck, 1994) and (Detert and Kotani, 2013) we run the regression

$$\frac{P_{c,t} - P_{c,t-1}}{P_{c,t-1}} = a + bP_{c,t-1} + e_t \tag{10}$$

where $a = \eta \bar{P}_c \Delta t$, $b = -\eta \Delta t$ and $e_t = \sigma \epsilon_t \sqrt{\Delta t}$ (taking the variance on both sides and using $\epsilon_t \sim N(0, 1)$, this implies σ=Standard Error of the regression). Estimates for GMR process are given in table (2). We show the path for Quarterly data from 1980 to 2016 and sample simulated paths for GBM and GMR in figure (4). The initial price in our data in 1980 was US \$ 40.26 per ton of coal. We however convert the figure to Rs./ton for our analysis given other data for India. Increases in coal prices were seen during the early 1980's, 2008 and 2010-11 with the maximum value reached in the third quarter of 2008 at US\$ 174.43. The path for GBM shows the fluctuating nature of global coal prices over time while that for GMR demonstrates convergence towards a long term average.

3.2 Framework

We posit a log-linear relationship between reduction in cost per unit of wind and solar technologies and (i) the cumulative installed capacity and (ii) cumulative investment expenditures ((Klaassen et al., 2005), (Lee and Shih, 2010)). We combine the unit costs of solar PV, solar rooftop, solar thermal and wind over the years and multiplying them with the cor-

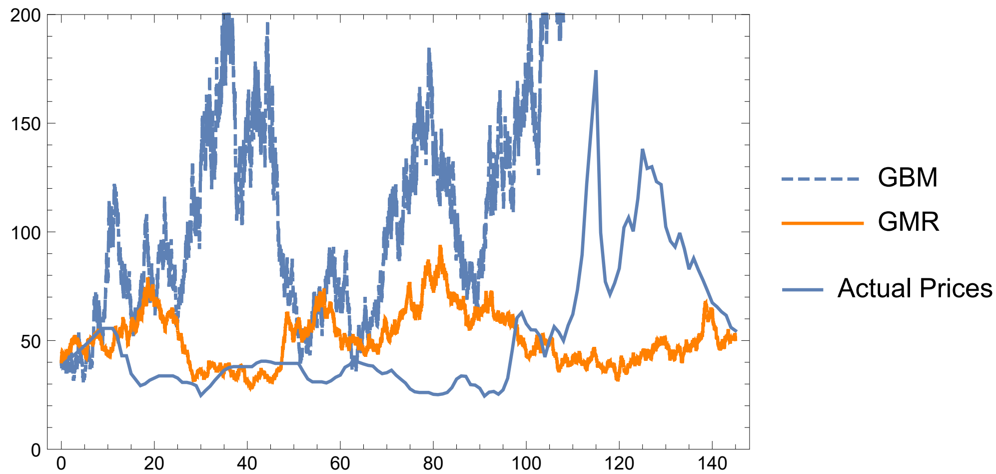


Figure 4: Coal Prices (US \$/ton): Data and Simulated GBM and GMR Paths

responding shares of these technologies of the total installed capacities of renewable energies, we arrive at an aggregate index of the unit cost of wind and solar. For cumulative installed capacities and investment expenditures, we also consider an aggregate index combining the figures for wind and solar. In this work, we measure unit cost as prices (tariffs) of electricity in Rs./KWh, cumulative installed capacity in GW and cumulative investment expenditures in billions of Rupees.[12] We study the trend in wind and solar prices in India and not their costs. However, with tariff-based competitive bidding, we think that producers and project developers do not have an incentive to offer bids too different from their levelized costs. We have the equation

$$C_t = AX_t^{-\alpha} Y_t^{-\beta} \tag{11}$$

where C_t is unit cost of electricity from wind and solar, A is specific cost at unit cumulative capacity and unit investment expenditure, X_t represents cumulative installed capacity, Y_t denotes cumulative investment expenditure and α and β are the learning-by-doing and learning-by-searching indices respectively. The learning-by-doing and the learning-by-searching rates are calculated as $(1 - 2^{-\alpha})$ and $(1 - 2^{-\beta})$ respectively. They capture the

[12](Klaassen et al., 2005) measure unit cost as investment costs (US \$/KW) while (Siddiqui et al., 2007) use cumulative energy produced (terawatt hours-TWh). For a meta-analysis of the literature on learning curves or experience curves for electricity supply technologies and the various specifications used, see (Rubin et al., 2015).

reduction in unit cost when cumulative installed capacity or cumulative investment expenditure is doubled. For example, if the learning-by-doing rate is 10%, it implies that when cumulative installed capacity is doubled, the unit cost falls to 90% of the original cost, i.e. a 10% reduction. A similar explanation follows for the learning-by-searching rate.[13] We report the learning-by-doing and learning-by-searching indices and estimates of other parameters used in our model in table (3). Taking the log of equation (11) we get[14]

$$lnC_t = lnA - \alpha lnX_t - \beta lnY_t \tag{12}$$

where ln denotes the natural logarithm.

3.3 Policy Benefit Evaluation Model

3.3.1 Basic Model

We construct a policy benefit evaluation model to find the overall policy value of India producing 25% of its electricity from wind and solar by 2030. This is given the share of hydro and nuclear and gas remain constant such that they meet the remainder of the 40% of non-fossil fuel sources in India's Paris Agreement targets. We denote year 0 as 2014 and take 2030 as the terminal year ($T = 16$) and evaluate the option for the Indian government to invest in additional wind and solar in any period between today and the end of the decision horizon. Electricity demand is expected to grow in India because of rising industrial production and transport demand ((Muneer et al., 2005)) and we assume net electricity demand growth to be at 7% as in (Buckley and Sharda, 2015).[15] Figure (5) explains the underlying problem.

[13] We calculate the learning-by-searching rate for wind and solar technologies as 7.3% and the learning-by-doing rates for solar PV, solar rooftop and wind to be 9.4%, 8.2% and 7.4% respectively (see (Lee and Shih, 2010) and (Lin and Wesseh, 2013) for learning rates for Taiwan and China respectively). The learning-by-doing rate for solar thermal technologies is zero due to negligible additions in solar thermal capacities which has resulted in its tariff being almost constant over recent years.

[14] We do not include an error term as in (Klaassen et al., 2005) and (Lee and Shih, 2010) for simplicity.

[15] Growing electricity demand for India also implies electricity generation from coal to increase in coming years but its share in total electricity generation to decrease because of it being substituted by other sources. The Indian government has goals to increase domestic coal production and there is the possibility of rising

Each of the curves in figure (5) show the possible paths of growth in electricity share of wind

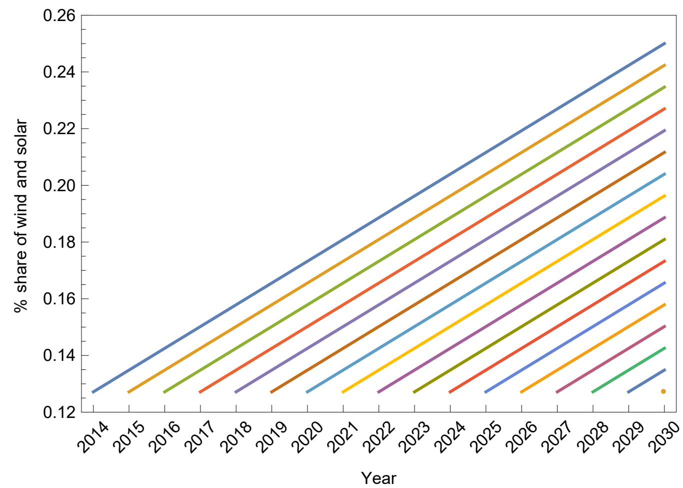


Figure 5: Wind and solar penetration through 2030

and solar if deployment is carried out in year 0 = 2014, year 1 = 2015, year 2 = 2016 and so on. That is to say, if the social planner exercises the option to deploy in additional wind and solar energies in 2014, its share in total electricity generated rises to 25% by 2030 from the expected share of 12.72%. Consequently, if deployment is done later in 2015 or 2016, the share of solar and wind reaches 24.23% and 23.46% respectively. Based on the binomial lattices in figures (2) and (3), the value of the option of deployment is calculated using the process of backward induction ((Dixit and Pindyck, 1994)). As in (Siddiqui et al., 2007), we assume the price of wind and solar to be falling until the time of deployment. This may be considered a limitation of the model. We start from the year 2030 assuming the option to deploy additional wind and solar was not exercised before and the share of renewables is at 12.72%. Earlier deployment gives the benefit of India reaching its Paris targets and enjoying cost savings from reduced coal use and lower total externality costs. However, the solar and wind price falls even further with later deployment but reaching domestic and international targets are compromised. With global coal prices $P_{c,t}$ (equations (1) and (6)) being our stochastic variable, we denote $W(k, i, r, j)$ the options value of deployment of additional solar and wind in period k given the number of upward coal price movements i, number of

coal imports over coming years.

research expenditures $r \leq k$ and that deployment was undertaken in period $j \leq k$. The policy value without deployment and with the option to deploy or continue with promotion policies depending on respective expected future benefits is given by $V(k,i,r)$ with k, i, r as before ((Siddiqui et al., 2007), (Lee and Shih, 2010)).

With deployment:

$$W(k,i,r,j) = [p_e q_{exc}(j,k) l_1 - E_c q_{exc}(j,k) + (p_{fit} - c_{ws}(k,r)) q_{ews}(j,k)] + P_{c,t}(k,i) Q_c(k) \\ + \rho \left(pW(k+1,i+1,r,j) + (1-p) W(k+1,i,r,j) \right) \tag{13}$$

Without deployment:

$$V(k,i,r) = max \begin{cases} W(k,i,r,j); \\ -R + \rho \left(pV(k+1,i+1,r+1) + (1-p) V(k+1,i,r+1) \right) \end{cases} \tag{14}$$

Equation (13) shows savings arising from greater deployment of wind and solar in addition to the cost for using coal to generate electricity. p_e and $q_{ews}(j,k)$ denote the price of electricity and the amount of electricity which is produced from wind and solar towards India meeting its Paris targets. p_{fit} is the combined average Feed-in-Tariff (FIT) for wind and solar power projects (we explain in detail in the next subsection).[16] $q_{exc}(j,k)$ captures the *extra* amount of electricity that is produced from coal and lignite: this variable takes the value 0 if Paris targets are met (or wind and solar share equals 25% in figure 5) to a maximum of 12.28% if additional wind and solar energies are not deployed. Similarly, $Q_c(k)$ is the *extra* amount of coal needed to produce the additional electricity from coal and lignite.[17] The capacity utilization factor of coal is captured by l_1 and total externality cost from coal-fired plants used for power generation is denoted by $E_c q_{exc}(j,k)$ where E_c is the per unit externality cost ((Cost

[16] We assume p_e to be constant. Data from (Power Finance Corporation, 2015). We attribute the price of electricity as that for electricity for coal and lignite fired power plants due to lack of official data specifically for electricity price paid to these plants. Although far from complete, there is official data for some states for FITs.

[17] $Q_c(k)$ also takes on a value of 0 if share of wind and solar equals 25%. $Q_c(k)$ is calculated using the average amount of coal needed to generate a GWh of electricity.

Assessment of Sustainable Energy Systems, 2008)).[18] Our variable of interest is the price of wind and solar energies $c_{ws}(k,r)$ which is falling with both increasing installed capacity over time and increasing research expenditures. The net cost of support of additional wind and solar energies is thus given by the difference of p_{fit} and $c_{ws}(k,r)$ which is increasing. $W(k,i,r,j)$ depends on its value one period after discounted using the rate of discount ρ and up and down probabilities defined as p and $1-p$ respectively (varying p and $1-p$ for mean reversion). Given equation (13), equation (14) is also calculated backwards beginning at T such that the value of future promotion policies is the maximum of the value of deployment and spending a fixed cost of R. We can solve for values of previous periods given the value for one period after and comparing with the option to deploy. The value function $V(k,i,r)$ thus compares the expected benefits from deployment or continuation for the social planner. After computing all of $W(k,i,r,j)$, we then get the overall real options value for time 0 as

$$V(0,0,0) = max \begin{cases} W(0,0,0,0); \\ -R + \rho\left(pV(1,1,1) + (1-p)V(1,0,1)\right) \end{cases} \tag{15}$$

where $V(0,0,0)$ is the policy value at year 0 of India meeting its Paris Agreement targets.

3.3.2 Introducing Cost of Support

We introduce cost of support of additional wind and solar technologies in form of FIT which means a minimum guaranteed price per unit of electricity paid to grid-connected renewable energy projects and solar rooftops. While grid-connected projects of usually 1 MW and above are those connected to the network of the distribution or transmission utilities to sell electricity directly to the grid, incentives such as FIT and a separate Generation Based Incentive (GBI) are also available for solar and wind power producers (not grid-connected) for sale of power to a public or private distribution licensees within a state ((Government

[18] The other way of measuring externality could be from CO_2 emissions from fuel combustion from electricity and heat production (from using coal). See (International Energy Agency, 2016). The problem is that data on price of CO_2/ton for India is hardly available.

of West Bengal, 2012), (Government of Tamil Nadu, 2012), (Government of Gujarat, 2009), (Government of Gujarat, 2013)).[19] While the benefit of FIT is offered by respective states and is administered by State Electricity and Regulatory Commissions (SERCs) for each state, GBI is an incentive (much smaller in proportion to FIT) which is offered by the central government and if applicable, is over and above the benefit of FIT. In this work, we consider the total cost of support of benefits of FIT and GBI borne by the central and state governments and its effect on the time of deployment of additional wind and solar technologies in view of India's national and international targets. India also plans to invest US $ 50 billion in order to upgrade its transmission and distribution grid and implement a net metering program which allows solar rooftops to feed surplus power to the grid and obtain FIT benefits ((Buckley and Sharda, 2015)). We arrive at a figure of Rs. 6.439/KWh (US $ 10.13c/KWh) as the combined average FIT for wind and solar power projects.

4 Results

4.1 Policy Value

The overall policy values or V at time 0 from equation (15) for GBM and GMR are shown in table (4). The drift and uncertainty associated with GBM implies a higher overall policy value at Rs. $24,029$ billion compared to Rs. $19,116$ billion if coal prices evolve according to GMR. The value of existing wind and solar technologies is computed supposing that $c_{ws}(k,r)$ is constant over time and that additional wind and solar is deployed whenever its cost falls below that of the stochastic coal price. It is interesting to note that even in absence of future promotion policies of investment expenditures and capacity additions, stochastic

[19] In cases when a solar or wind power producer (not grid-connected) sells power to a state or private distribution licensee, the rates of purchase either pertain to officially determined rates or mutually agreed rates between the producer and the distribution licensee. Power purchase agreements may extend up to 25 years in this case and the wind or solar power developer pays for the entire cost of construction and power evacuation facilities and the acquisition of land up to the interconnection point with the distribution licensee substation ((Government of Andhra Pradesh, 2015a), (Government of Andhra Pradesh, 2015b)).

world coal prices give existing wind and solar technologies a sufficiently high value of Rs. $10,343$ and Rs. $6,110.4$ billion respectively.This can be contrasted to losses for state utilities selling electricity directly to consumers (state utilities source majority of their power from coal fired power plants and have limited renewable purchase obligation targets) which were Rs. 637.65 Billion in 2013-14 ((Power Finance Corporation, 2015)). We find the value of future promotion policies as the difference between the overall real options value and the value of existing wind and solar: for similar reason of drift and uncertainty in case of GBM, value of future promotion policies is also higher compared to that for GMR.

4.2 Trigger Price and Cumulative Cost of Deployment

We compute the 'trigger' price of coal which triggers deployment of additional wind and solar technologies today. (Dixit and Pindyck, 1994) explain this price to be that when the value of the option at the end of the decision horizon equals the value of the option today or the value of waiting falls to zero. (Detert and Kotani, 2013) find trigger prices for Mongolia switching to renewable energies in its electricity generation mix from traditional use of coal and diesel. Using the policy benefit evaluation model from above we find the trigger price of coal where the social planner finds the value of deployment of additional wind and solar to be higher than that of continuing with cumulative capacity additions and cumulative investment expenditures. We show the trigger prices in tables (5) and (6).

We introduce the concept of cumulative cost of deployment which is the sum of the net cost of support times the electricity generated from wind and solar energies towards India meeting its domestic and international targets, i.e. $\sum(p_{fit} - c_{ws}(k,r))q_{ews}(j,k)$. The net cost of support rises over time the longer the social planner waits to exercise deployment but additional electricity produced from wind and solar also takes a lower trajectory until the end of the decision horizon as shown in figure (5). However, the effect of paying support for a longer time dominates and we find the cumulative cost of support to increase. This is a difference from the work of (Lee and Shih, 2010) and (Lin and Wesseh, 2013) who consider maximizing the overall policy value of the renewable energy investment program adjusting the FIT rate. In increasing the FIT rate slowly from that which is fixed by the government (of Taiwan and China respectively), the papers find the optimum FIT which should be fixed by the government.[20] In case of India, the FITs for wind and solar energies are actually falling and GBIs especially for wind have been put a halt. This has resulted in a small decline in number of projects commissioned and power purchase agreements signed ((Economic Times, 2017), (Economic Times, 2018a), (Economic Times, 2018b)). We think one of the reasons for fall in FITs in India is a decline in levelized costs for wind and solar which supposedly need less support from the government. But solar installations (installed wind capacity far exceeds that of solar with significantly less capacity targets by 2021-22) have not been as fast for India to meet its domestic targets and the solar rooftop sector is not very developed.[21]. We propose that the cumulative cost of deployment has an important effect on the timing of deployment of additional wind and solar because it puts an additional strain on the resources of a relatively poor economy. In addition, widespread deployment of solar electricity in the long run would affect industries such as consumer electronics (whose demand is expected to rise as the economy grows) which competes with solar for use of scarce minerals, e.g. semiconducting materials like indium which is used for manufacturing of liquid crystal displays ((Steinbuks et al., 2017)). We modify equation (14) to include the cumulative cost of deployment as

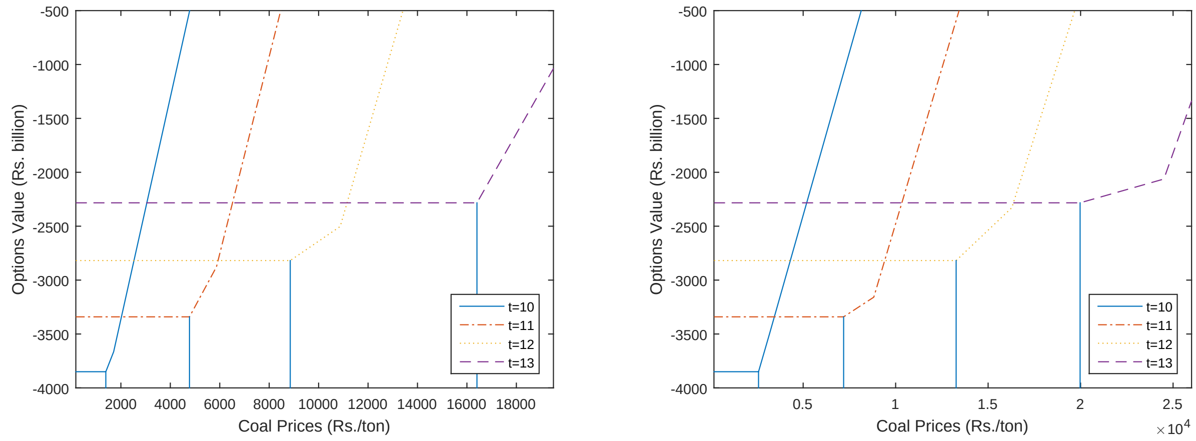
$$V(k,i,r) = max \begin{cases} W(k,i,r,j) - D(k,i,r,j); \\ -R + \rho\left(pV(k+1,i+1,r+1) + (1-p)V(k+1,i,r+1)\right) \end{cases} \tag{16}$$

where $D(k,i,r,j)$ denotes the cumulative cost of deployment with k, i, r, j as before. Table (3) shows the rising values of the cumulative cost of deployment. The overall real options

[20](Lee and Shih, 2010) maximize the ratio of the overall policy value of the renewable energy development program to that of cumulative research expenditures.

[21]See (Bridge to India, 2016), (Bridge to India, 2017) for comparison of solar capacity installations in India and in other countries.

value is similarly modified as in equation (15). Results as in table (4) would be to reduce the overall policy value and values of existing wind and solar and of future policies: we however report the more interesting case of the effect of D on the trigger price. Table (5) reveals the trigger price which forces the social planner to deploy additional wind and solar technologies today at $t = 0$ does not exist for GBM and that it is very high for the case of GMR at Rs. $83,532$ (US \$ $1,314.2$) per ton of coal. So, the policy of continuing with future additions to wind and solar capacities and research expenditures is undertaken today for the case of GBM and effectively for all coal prices for GMR by the social planner until the option to deploy is exercised when coal prices reach a very high level. We however find that the option to deploy would be exercised for $t = 1$ to $t = 16$ (the end of the decision horizon or T) for all prices for both GBM and GMR. We note the lowest price in our data as Rs. 177.8 (US \$ 2.8) per ton of coal for GBM and Rs. 181.4 (US \$ 2.9) for GMR as trigger prices for these cases. Results are qualitatively similar until $t = 9$ when the cumulative cost of deployment is included in table (6): the social planner chooses to continue today instead of deployment for GBM and exercises deployment in case of GMR at a very high price per ton of coal. So, in the best scenario, from figure 5, we conclude that the share of wind and solar in the electricity generation mix would reach 24.23% which is not very far from India's Paris Agreement targets. Intuitively given the policy to continue with promotion policies today, deploying additional renewable energies at even very low global coal prices tomorrow and the day after is justified as the price of wind and solar keeps falling until the time of deployment. We report trigger prices from $t = 10$ onwards which are lower (except for $t = 16$) for GBM in contrast to GMR because of higher uncertainty associated with GBM in place of prices converging towards a long term average. If deployment is exercised at $t = 10$, the share of wind and solar reaches 18.09% by 2030. We show a threshold curve or a "free boundary" ((Dixit and Pindyck, 1994)) in figure (7) such that for each period, if coal prices are above the boundary, the option to deploy is exercised–otherwise the social planner chooses to continue with future policies. The free boundary is non-decreasing since approaching the end of the

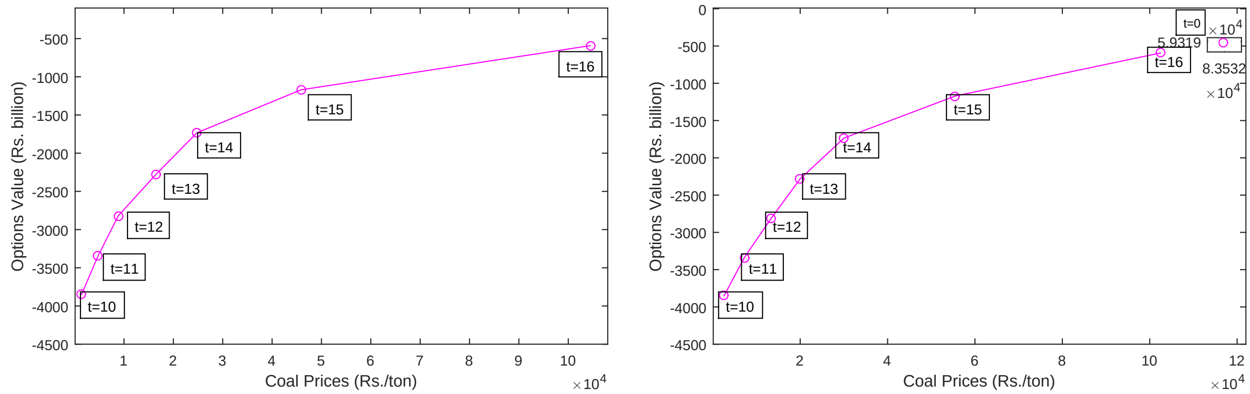


(a) GBM

(b) GMR

Figure 6: Value functions for GBM and GMR with cost of deployment

decision horizon entails the social planner would wait longer and for a higher global coal price before exercising the option to deploy additional wind and solar energies. The trigger price increases from Rs. $2,586.6$ (US \$ 40.7) for $t = 10$ to Rs. $102,480$ (US \$ $1,612.3$) per ton of coal for GMR and from Rs. $1,390.3$ (US \$ 21.9) for $t = 10$ to Rs. $104,460$ (US \$ $1,643.4$) per ton of coal for GBM. As an example, we show the value functions for cases of GBM and GMR in figure (6). The overall value of additional wind and solar energies rises with coal prices given the possibility of coal becoming costlier in future and a rising cost of pollution. The points of kink depict the trigger prices such that the option value keeps rising after deployment for periods $t = 10$ to $t = 13$ considered in the figure. Intuitively, the free boundaries in figure (7) are obtained by connecting the points of kink in figure (6). Given a very high trigger price today for GMR, it is shown as a separate box in the top-right corner inside figure (7)(b). We see for $t = 10$ for GBM, the option to deploy would be exercised for a price of coal greater or equal to Rs. $1,390.3$ per ton while the trigger price for $t = 14$ is Rs. $24,755$ per ton of coal. Similarly, we observe trigger prices for various periods for the case of GMR.



(a) GBM

(b) GMR

Figure 7: Free boundaries for GBM and GMR with cost of deployment

5 Discussion

We find the overall value of additions to solar and wind energies in context of India's ambitious domestic targets and its Paris Agreement goals using a real options approach. The work is interesting given installed capacities for both wind and solar energies have risen rapidly as seen in figure 1 and new investments in wind and solar energies (as a total of venture capital and private equity investments, public and private R&D expenditures and small distributed capacity investments) have also increased from Rs. 156 billion to Rs. 572 billion between 2004 to 2015 ((Bloomberg New Energy Finance, 2017), (Bloomberg New Energy Finance, 2018)). In addition, solar and wind tariffs have been falling in India as shown by power purchase agreements offered to wind and solar project developers because of their competitive bids. We proceed with our analysis using coal prices as the stochastic variable ((Detert and Kotani, 2013)) and using a two-factor model of (Klaassen et al., 2005) to model the decline in prices of wind and solar.

Future work could consider the effects of scale economies and input prices for India as part of the learning curve model. While there have been studies regarding the effect of size of the wind farm and its input costs for China ((Qiu and Anadon, 2012)), detailed information on the number of wind farms and their respective sizes for India is not available. The other issue is that research could overstate the effect of scale economies for wind energies given lower efficiency factors and capital costs in India in comparison to other parts of the world. (Buckley and Sharda, 2015) report capital costs for wind at US $ 1 million for 1 MW of capacity because of older and less efficient technologies with the capacity utilization factor at 25%. On the other hand, with a global average installation cost of wind between US $ 1.5-2 million per MW of capacity, efficiency factors range from 30-35% for the US and Australia and upwards of 40% for some sites in Brazil and New Zealand.[22] With India planning to build taller wind turbines, the efficiency factor would increase however dampening the reduction in wind prices for consumers (see footnote 9). We do not include the effect of domestic module manufacturing on solar prices in India since most of the module manufacturing capacity is obsolete and uncompetitive and module prices from China, the largest source of module imports at over 80%, also increased over 2017 because of higher import duties and other reasons ((Bridge to India, 2017), (Economic Times, 2018a)). One possible avenue for extension could be to include the investment in solar parks by large developers where the land for the park and basic acess roads are built by the government but the developer bears all expenses for building the connection line until the distribution licensee or offtaker substation which in turn sells power to consumers ((Government of West Bengal, 2012)). There also exists a significant number of central and state schemes offering financial support for building solar parks ((Government of Karnataka, 2014), (Bridge to India, 2017)). Some other ideas could be to analyze the effect of scarcity of water in the drier states of India of Gujarat and Rajasthan with a significant number of solar installations: the cost of cleaning and maintaining solar panels is higher for these states and it would be interesting to see whether incomes increase due to greater access to electricity or if the cost of diverting water from essential domestic and agricultural uses to maintaining solar panels is high enough. The effect of the increasing operating efficiency of coal-fired power plants due to restructuring of the electricity sector in India as proposed in the Act (Malik, 2012) and a greater use of nuclear

[22]Capacity utilization factors are even higher for off-shore wind farms ((International Renewable Energy Agency (IRENA), 2015)). India does not have any such wind farm yet.

power in India could help the country achieve Paris targets without huge investments in wind and solar energies while reducing coal imports. Finally, the effect of subsidized electricity prices is out of the scope for the current version of the paper. Electricity prices are highly subsidized in India especially for agricultural consumers and taking this into account would only increase the electricity price which we expect would alter the trigger price downwards.

6 Conclusions

The question addressed in this work is if India can meet its ambitious domestic targets and Paris Agreement goals. Domestic targets, by the year 2021-22, for capacity installations in wind and solar energies were scaled up from 50 GW to 60 GW and 20 GW to 100 GW respectively. This was part of the Budget 2015 targets announced by the current government. As part of India's Paris climate agreement targets in 2015, it plans to produce 40% of its electricity from non-fossil fuel sources and reduce its emission per unit of GDP by 33-35% from 2005 levels by the year 2030. We assume global coal prices following the processes of GBM and GMR and conclude that wind and solar technologies could help India reach its targets to a large extent if promotion policies of capacity additions and investment expenditures are undertaken for some time. Cumulative capacity additions and cumulative investment expenditures help reduce prices of wind and solar energies which gives a high real options value for these promotion policies. We include support schemes such as FIT and GBI from the central and state governments and the planner solution remains unchanged. In addition, solving for trigger prices of when additional wind and solar energies would be deployed for cases of GBM and GMR, the trigger price is found to be non-decreasing as we approach the end of the decision horizon. Trigger prices in general are also higher for GBM in contrast to GMR because of the drift and uncertainty associated with the process. However, our solution shows that the social planner should only exercise the option to deploy wind and solar after some time periods given promotion policies of investments in these energies have been able to reduce their prices effectively.

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References

Carlos Bastian-Pinto, Luiz Brando, and Warren J. Hahn. Flexibility as a source of value in the production of alternative fuels: The ethanol case. *Energy Economics*, 31(3):411 – 422, 2009. ISSN 0140-9883. doi: https://doi.org/10.1016/j.eneco.2009.02.004. URL http://www.sciencedirect.com/science/article/pii/S0140988309000334.

Carlos Bastian-Pinto, Luiz E Brandão, and Warren J Hahn. A non-censored binomial model for mean reverting stochastic processes. In *Annual International Conference on Real Options*, volume 14, pages 1–24, 2010.

Fischer Black and Myron Scholes. The pricing of options and corporate liabilities. *Journal of Political Economy*, 81(3):637–654, 1973. ISSN 00223808, 1537534X. URL http://www.jstor.org/stable/1831029.

Bloomberg New Energy Finance. Global Trends in Renewable Energy Investment 2017. *Frankfurt School-UNEP Centre/BNEF 2017*, UN Environment Programme, Frankfurt School-UNEP Collaborating Centre for Climate & Sustainable Energy Finance, Bloomberg New Energy Finance, 2017. URL http://www.fs-unep-centre.org. Accessed: 2018-07-01.

Bloomberg New Energy Finance. Global Trends in Renewable Energy Investment 2018.

Frankfurt School-UNEP Centre/BNEF 2018, UN Environment Programme, Frankfurt School-UNEP Collaborating Centre for Climate & Sustainable Energy Finance, Bloomberg New Energy Finance, 2018. URL http://www.fs-unep-centre.org. Accessed: 2018-07-01.

Svetlana Boyarchenko and Sergei Levendorskii. Practical guide to real options in discrete time. *International Economic Review*, 48(1):311–342, 2007. ISSN 00206598, 14682354. URL http://www.jstor.org/stable/4541969.

Bridge to India. India Solar Handbook, 2016. *Bridge to India*, Bridge to India, 2016.

Bridge to India. India Solar Handbook, 2017. *Bridge to India*, Bridge to India, 2017.

Tim Buckley and Jai Sharda. India's Electricity Sector Transformation. *Institute for Energy Economics and Financial Analysis*, 2015.

Central Electricity Authority. Growth of Electricity Sector in India From 1947-2015. *Central Electricity Authority*, Ministry of Power, Government of India, April 2015. Accessed: 2018-03-01.

Central Electricity Authority. Growth of Electricity Sector in India From 1947-2017. *Central Electricity Authority*, Ministry of Power, Government of India, May 2017. Accessed: 2018-03-01.

Central Statistics Office. Energy Statistics. *Central Statistics Office, Ministry of Statistics and Programme Implementation*, Government of India, 2015.

Central Statistics Office. Energy Statistics. *Central Statistics Office, Ministry of Statistics and Programme Implementation*, Government of India, 2016.

Ujjayant Chakravorty, Martino Pelli, and Beyza Ural Marchand. Does the quality of electricity matter? Evidence from rural India. *Journal of Economic Behavior & Organization*, 107:228–247, nov 2014. doi: 10.1016/j.jebo.2014.04.011. URL https://doi.org/10.1016%2Fj.jebo.2014.04.011.

Cost Assessment of Sustainable Energy Systems. Cross-country Comparison of the Case Studies under WP7. *Cost Assessment of Sustainable Energy Systems (CASES)*, WP7 Report on the comparative assessment of fuel cycle costs and methodological challenges across the participating countries, 2008. Accessed: 2016-08-01.

CRISIL Ratings. Wind power tariffs sustainable around Rs 3 per unit Lower payment and offtake risks, falling generation costs improves risk-return. *CRISIL An S&P Global Company*, 2018. URL https://www.crisil.com/en/home/newsroom/press-releases/2018/06/wind-power-tariffs-sustainable-around-rs-3-per-unit.html. Accessed: 2018-08-01.

Neal Detert and Koji Kotani. Real options approach to renewable energy investments in Mongolia. *Energy Policy*, 56:136–150, may 2013. doi: 10.1016/j.enpol.2012.12.003. URL https://doi.org/10.1016%2Fj.enpol.2012.12.003.

Avinash K. Dixit and Robert S. Pindyck. *Investment under Uncertainty*. Princeton University Press. Princeton University Press, 1994. ISBN 0-691-03410-9.

Sunita Dubey, Siddharth Chatapalliwar, and Srinivas Krishnaswamy. Electricity for All in India Why coal is not always king. *Vasudha Foundation*, October 2014.

Economic Times. Wind tariff drops to new low of Rs. 2.43/unit. *Economic Times*, 2017. URL https://economictimes.indiatimes.com/industry/energy/power/wind-tariff-drops-to-new-low-of-rs-2-43/unit/articleshow/62205511.cms. Accessed: 2018-08-01.

Economic Times. Solar tariffs once again hit all-time low of Rs 2.44 a unit at SECI auction. *Economic Times*, 2018a. URL https://economictimes.indiatimes.com/industry/

energy/power/solar-tariffs-once-again-hit-all-time-low-of-rs-244-a-unit-at-seci-auction/articleshow/64834531.cms. Accessed: 2018-08-01.

Economic Times. Wind tariffs end descend, edge up to Rs. 2.44/unit. *Economic Times*, 2018b. URL https://economictimes.indiatimes.com/industry/energy/power/wind-tariffs-end-descend-edge-up-to-rs-2-44/unit/articleshow/62914286.cms. Accessed: 2018-08-01.

Federal Reserve Bank of St. Louis. FRED Graph Observations. *Federal Reserve Economic Data, Economic Research Division*, 2016. Accessed: 2016-08-01.

Government of Andhra Pradesh. Andhra Pradesh Solar Power Policy-2015 and Energy Department - Policy on net metering for solar grid interactive roof-top and small SPV power plants in the State. *Energy, Infrastructure and Investment Department*, February 2015a.

Government of Andhra Pradesh. Andhra Pradesh Wind Power Policy-2015. *Energy, Infrastructure and Investment Department-Development of Wind Power in Andhra Pradesh*, February 2015b.

Government of Gujarat. Solar Power Policy–2009. *Energy and Petrochemicals Department*, January 2009.

Government of Gujarat. Wind Power Policy–2013. *Energy and Petrochemicals Department*, July 2013.

Government of India. Guidelines for Selection of New Grid Connected Solar Power Projects, Batch-II. *Jawaharlal Nehru National Solar Mission*, Ministry of New and Renewable Energy (MNRE), August 2011.

Government of India. Guidelines for Development of Solar Parks. *Jawaharlal Nehru National Solar Mission*, Ministry of New and Renewable Energy (MNRE), February 2016.

Government of Karnataka. Karnataka Renewable Energy Policy 2009-2014. *Department of Energy*, May 2010.

Government of Karnataka. Solar Policy 2014-2021. *Department of Energy*, May 2014.

Government of Tamil Nadu. Tamil Nadu Solar Energy Policy 2012. *Energy Department*, January 2012.

Government of West Bengal. Policy on Co-generation and Generation of Electricity from Renewable Sources of Energy. *Department of Power and Nonconventional Energy Sources*, June 2012.

Daniel Hach and Stefan Spinler. Capacity payment impact on gas-fired generation investments under rising renewable feed-in — A real options analysis. *Energy Economics*, 53: 270–280, jan 2016. doi: 10.1016/j.eneco.2014.04.022. URL https://doi.org/10.1016%2Fj.eneco.2014.04.022.

J. Hull. *Options, Futures, and Other Derivatives*. Options, Futures, and Other Derivatives. Prentice Hall, 2012. ISBN 9780132777421. URL https://books.google.com.mx/books?id=LzBTpwAACAAJ.

International Energy Agency. International Energy Agency (IEA), CO_2 Emissions from Fuel Combustion. *International Energy Agency*, 2016. Accessed: 2018-03-01.

International Renewable Energy Agency (IRENA). Renewable Power Generation Costs in 2014. *International Renewable Energy Agency (IRENA)*, 2015. Accessed: 2018-01-10.

Frode Kjrland. A real option analysis of investments in hydropowerthe case of norway. *Energy Policy*, 35(11):5901 – 5908, 2007. ISSN 0301-4215. doi: https://doi.org/10.1016/j.enpol.2007.07.021. URL http://www.sciencedirect.com/science/article/pii/S0301421507003138.

Ger Klaassen, Asami Miketa, Katarina Larsen, and Thomas Sundqvist. The impact of r&d

on innovation for wind energy in denmark, germany and the united kingdom. *Ecological Economics*, 54(2):227 – 240, 2005. ISSN 0921-8009. doi: https://doi.org/10.1016/j.ecolecon.2005.01.008. URL http://www.sciencedirect.com/science/article/pii/S0921800905000340. Technological Change and the Environment.

Shun-Chung Lee and Li-Hsing Shih. Renewable energy policy evaluation using real option model – the case of taiwan. *Energy Economics*, 32(Supplement 1):S67–S78, 2010. URL http://EconPapers.repec.org/RePEc:eee:eneeco:v:32:y:2010:i:supplement1:p:s67-s78.

Boqiang Lin and Presley K. Wesseh. Valuing Chinese feed-in tariffs program for solar power generation: A real options analysis. *Renewable and Sustainable Energy Reviews*, 28:474–482, dec 2013. doi: 10.1016/j.rser.2013.08.043. URL https://doi.org/10.1016%2Fj.rser.2013.08.043.

Kabir Malik. The Impact of Electricity Sector Restructuring on Coal-fired Power Plants in India. *Job Market Paper*, Department of Agricultural and Resource Economics, University of Maryland, 2012.

Robert C. Merton. Theory of Rational Option Pricing. *Bell Journal of Economics*, 4(1):141–183, Spring 1973. URL https://ideas.repec.org/a/rje/bellje/v4y1973ispringp141-183.html.

Ministry of Coal. Coal Directory of India 2013-14. *Coal Statistics*, Ministry of Coal, Government of India, 2015.

Ministry of Power. Electricity Act, 2003, 2018. URL https://powermin.nic.in/en/content/electricity-act-2003. Accessed 2018-08-01.

Tariq Muneer, Muhammad Asif, and Saima Munawwar. Sustainable production of solar electricity with particular reference to the Indian economy. *Renewable and Sustainable*

Energy Reviews, 9(5):444–473, oct 2005. doi: 10.1016/j.rser.2004.03.004. URL https://doi.org/10.1016%2Fj.rser.2004.03.004.

Stewart C. Myers. Determinants of corporate borrowing. *Journal of Financial Economics*, 5 (2):147 – 175, 1977. ISSN 0304-405X. doi: https://doi.org/10.1016/0304-405X(77)90015-0. URL http://www.sciencedirect.com/science/article/pii/0304405X77900150.

Daniel B. Nelson and Krishna Ramaswamy. Simple binomial processes as diffusion approximations in financial models. *The Review of Financial Studies*, 3(3):393–430, 1990. doi: 10.1093/rfs/3.3.393. URL http://dx.doi.org/10.1093/rfs/3.3.393.

James L. Paddock, Daniel R. Siegel, and James L. Smith. Option valuation of claims on real assets: The case of offshore petroleum leases. *The Quarterly Journal of Economics*, 103(3):479–508, 1988. ISSN 00335533, 15314650. URL http://www.jstor.org/stable/1885541.

Power Finance Corporation. The Performance of State Power Utilities for the years 2011-12 to 2013-14. *Power Finance Corporation Ltd.*, Government of India, 2015. Accessed: 2018-08-01.

Yueming Qiu and Laura D. Anadon. The price of wind power in china during its expansion: Technology adoption, learning-by-doing, economies of scale, and manufacturing localization. *Energy Economics*, 34(3):772 – 785, 2012. ISSN 0140-9883. doi: https://doi.org/10.1016/j.eneco.2011.06.008. URL http://www.sciencedirect.com/science/article/pii/S0140988311001307.

Edward S. Rubin, Ins M.L. Azevedo, Paulina Jaramillo, and Sonia Yeh. A review of learning rates for electricity supply technologies. *Energy Policy*, 86:198 – 218, 2015. ISSN 0301-4215. doi: https://doi.org/10.1016/j.enpol.2015.06.011. URL http://www.sciencedirect.com/science/article/pii/S0301421515002293.

Gireesh Shrimali, Sandhya Srinivasan, Shobhit Goel, Saurabh Trivedi, and David Nelson.

Reaching India's Renewable Energy Targets Cost-Effectively. *A CPI-ISB Series*, Climate Policy Initiative Indian School of Business (ISB) Bharti Institute of Public Policy, April 2015.

Afzal S. Siddiqui, Chris Marnay, and Ryan H. Wiser. Real options valuation of US federal renewable energy research development, demonstration, and deployment. *Energy Policy*, 35(1):265–279, jan 2007. doi: 10.1016/j.enpol.2005.11.019. URL https://doi.org/10.1016%2Fj.enpol.2005.11.019.

Jevgenijs Steinbuks, Gaurav Satija, and Fu Zhao. Sustainability of solar electricity: The role of endogenous resource substitution and cross-sectoral responses. *Resource and Energy Economics*, 49:218 – 232, 2017. ISSN 0928-7655. doi: https://doi.org/10.1016/j.reseneeco.2017.05.005. URL http://www.sciencedirect.com/science/article/pii/S0928765517301483.

The World Bank. World Development Indicators, The World Bank. *The World Bank*, 2017. Accessed: 2018-03-01.

Lenos Trigeorgis. Real Options and Interactions With Financial Flexibility. *Financial Management*, 22(3):202–224, Fall 1993. URL https://ideas.repec.org/a/fma/fmanag/trigeorgis.html.

Konstantinos Venetsanos, Penelope Angelopoulou, and Theocharis Tsoutsos. Renewable energy sources project appraisal under uncertainty: the case of wind energy exploitation within a changing energy market environment. *Energy Policy*, 30(4):293 – 307, 2002. ISSN 0301-4215. doi: https://doi.org/10.1016/S0301-4215(01)00096-9. URL http://www.sciencedirect.com/science/article/pii/S0301421501000969.

Table 3: Baseline Parameters

Parameters	Values	Estimation
p_e (Rs./KWh)	4.37	Average of electricity prices for all regions and states across five regional grids as reported by SERCs ((Power Finance Corporation, 2015)).
q_{exc} (GWh)		Calculations using data from (Central Statistics Office, 2015),
$t = 0,..,16$	$0, ..416, 010$	(Central Statistics Office, 2016).
l_1	0.655	(Central Electricity Authority, 2015).
E_c (Rs./KWh)	4.22	(Cost Assessment of Sustainable Energy Systems, 2008).
$c_{ws}(0, 0)$ (Rs./KWh)	5.62	Data for capacity additions and tariffs and capacity utilization factors for wind and solar energies obtained from government sources and (Buckley and Sharda, 2015) and (Bridge to India, 2016), (Bridge to India, 2017) and (Shrimali et al., 2015). Data for investment expenditures in renewable energies from (Bloomberg New Energy Finance, 2017), (Bloomberg New Energy Finance, 2018). Using techniques in (Klaassen et al., 2005), we compute the learning indices (α, β) and obtain the price of wind and solar at time 0.
A (Rs./KWh)	7.25	Same as to compute $c_{ws}(0, 0)$.
α	0.115	Same as to compute $c_{ws}(0, 0)$.
β	0.109	Same as to compute $c_{ws}(0, 0)$.
q_{exws} (GWh)		Calculations using data from (Central Statistics Office, 2015), (Central Statistics Office, 2016) with estimated capacity additions and
$t = 0,..16$	$430, 710, ., 846, 720$	capacity utilization factors as obtained for $c_{ws}(0, 0)$.
$P_{c,t}(0, 0)$ (Rs./ton)	$4, 775.9$	(Federal Reserve Bank of St. Louis, 2016).
$Q_c(k)$ (Million Tons), $t = 0, ..16,$	$0, ..178.88$	Average amount of coal needed for a GWh of electricity calculated from (Ministry of Coal, 2015), (Central Statistics Office, 2015), (Central Statistics Office, 2016).
p_{fit} (Rs./KWh)	6.439	Various state government sources. See text.
D (Rs. billion)		
$t = 0,..16$	$696.89, ., 23, 434.15$	Obtained from state government sources as for the average combined FIT.
R (Rs. billion)	592.62	(Bloomberg New Energy Finance, 2017), (Bloomberg New Energy Finance, 2018).
T (years)	16	
Δt (years)	1	
ρ	0.975	(Detert and Kotani, 2013).

1 GWh= 10^6 KWh
Exchange Rate: 1 \$ US =Rs. 63.56, 1 Euro=Rs. 70.55 ((Federal Reserve Bank of St. Louis, 2016))

Table 4: Overall real options value (Rs. billion)

	Total Value	Value of existing wind & solar	Value of future policies
GBM	$24, 029$	$10, 343$	$13, 686$
GMR	$19, 116$	$6, 110.4$	$13, 005.6$

Table 5: Trigger prices Rs./ton

	$t = 0$		
GBM	$t = 0$	continue	
	$t = 1....t = 16(= T)$	deploy	177.8
GMR	$83,532$	–	
	$t = 1....t = 16(= T)$	deploy	181.4

Table 6: Trigger prices with cost of deployment Rs./ton

	$t = 0$	$t = 10$	$t = 11$	$t = 12$	$t = 13$	$t = 14$	$t = 15$	$t = 16(= T)$
GBM	–	$1,390.3$	$4,775.9$	$8,851.7$	$16,406$	$24,755$	$45,881$	$104,460$
	$t = 0$	continue						
	$t = 1,2,3$							
	$t = 4,5,6$							
	$t = 7,8,9$	deploy	177.8					
GMR	$83,532$	$2,586.6$	$7,187.8$	$13,271$	$19,973$	$30,060$	$55,502$	$102,480$
	$t = 1,2,3$							
	$t = 4,5,6$							
	$t = 7,8,9$	deploy	181.4					