Unpacking the Driving Forces of Historical Electricity Generation Cost Change In Korea : Market Forces vs Technological Learning

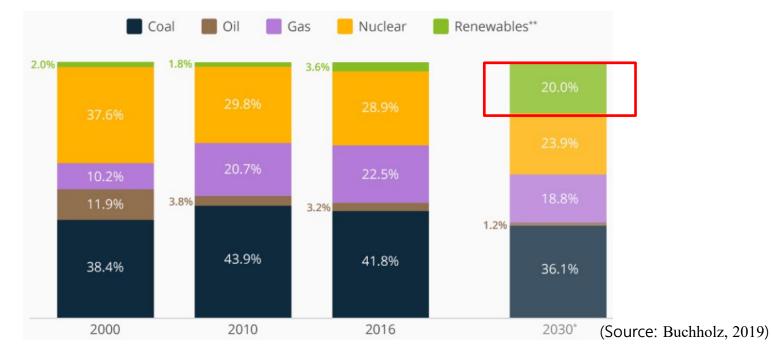
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# (1) Introduction

- Electricity generation in Korea (9<sup>th</sup> BPLE<sup>\*</sup>)
  - Promote low-carbon power generation technologies
  - Limiting additional unit of nuclear power plants
  - Conventional power generating sources will remain dominant in 2030

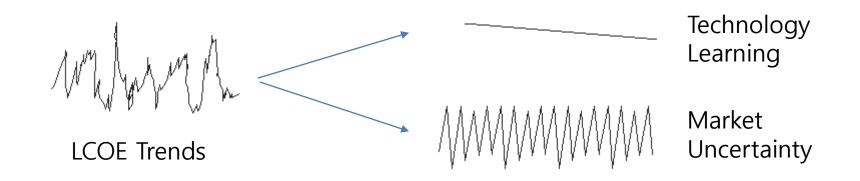


< Electricity generation share by technology in Korea >

\* 9th Basic Plan for Long-term Electricity Supply & Demand

# (1) Introduction

- Cost of decarbonizing energy system
  - Replacing coal with gas: Reduce emission, Increase volatility of cost
  - Renewable: Costly (up to now), Increase the energy self-sufficiency
- Research Question
  - Will renewable electricity generation likely to become cost-competitive?
  - How technology learning and market uncertainties affect the future LCOE?
  - What are enabling policy, technology, market condition for energy transition?



# (2) Literature Review

- LCOE (Levelized Cost Of Electricity)
  - Measure to compare cost-competitiveness of different generation sources
  - Fuel cost, O&M cost, Capital cost are converted in \$/kwh unit
- Historical LCOE

- Decades of empirical plant level cost data: McNerney et al. (2011), Koomey & Hultman (2007), Boccard (2014)

- Focus on construction cost: Grubler (2010), Lovering et al. (2016)
- Stochastic LCOE
  - Uncertainty in fuel price, carbon price, construction duration, renewable generation
  - Cross technology comparison: Heck et al. (2016), Lucheroni and Mari (2017)

- In-depth technology analysis: Aldersey-Williams & Rubert (2019), Geissmann & Ponta (2017)

- Contribution
  - Stochastic LCOE projection based on trends & distributions from historical data
  - Cross-technology comparison to draw implications in the context of energy transition

#### (3) Method

- Data
  - <u>Extensive plant-level data\*</u> for conventional technologies (Coal: Steam turbine using bituminous coal, Gas: Combined cycle)
  - Commercial scale renewable plants (Solar >100kW ; Wind >1MW unit)
  - Sources: KITA, EPSIS, KEPCO, KPX, and BNEF

(as of 2019)	CPP	CCGT	NPP	Solar	Wind
A. Number of plants in operation (GW)	60	187	26	N/A	N/A
	(36.9)	(32.5)	(21.8)	(8.1)	(1.3)
B. Number of plants	58	174	26	198	57
in analysis (GW)	(36.4)	(31.0)	(21.8)	(0.62)	(1.14)
Data coverage (B/A)	97.1%	93.0%	100%	N/A	N/A
	(98.6%)	(95.4%)	(100%)	(7.7%)	(87.8%)

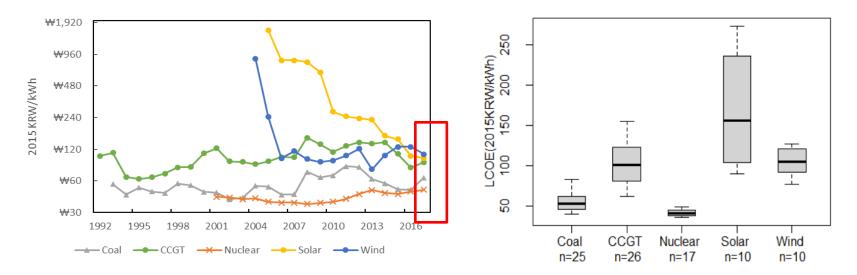
< Data coverage >

(Source: KPX)

\* Plant-level data is limited to construction cost while other data is technology-year-specific

## (4) Analysis

- LCOE trends
  - LCOE as of 2017: Nuclear < Coal < CCGT < Solar < Wind
  - Renewable sources are still expensive, but their LCOE is decreasing
- LCOE Volatility
  - LCOE of nuclear is stable while that of fossil-fuel based technologies are volatile
  - LCOE volatility of the CCGT was larger than that of Wind

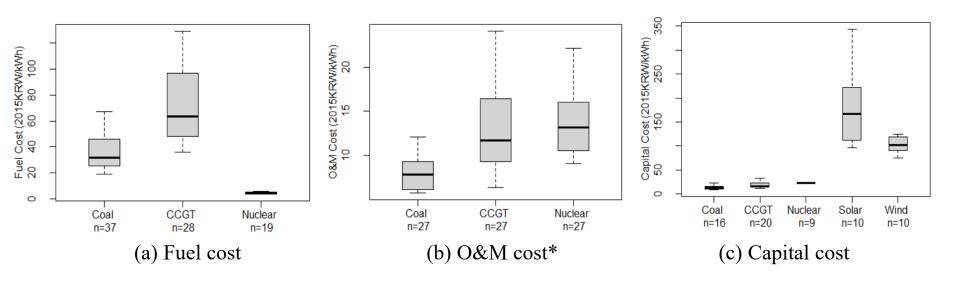


< LCOE trends and volatility of each technology>

#### (4) Analysis

- Source of volatility
  - Fuel cost: Fossil fuel import price (Coal, Gas)
  - O&M cost:
    - 1) Capacity factor change as a peak-load generator (CCGT)
    - 2) Increased maintenance due to enhanced safety regulations (Nuclear)

- Capital cost: Matured technologies show small volatilities while renewables show high volatilities



\* We could not get representative O&M cost data. We assumed O&M cost is proportional to capital cost for LCOE calculation

#### (4) Analysis

- Technology Learning
  - Learning rates were derived with construction cost accumulated capacity
  - Conventional technologies show negative learning
  - Solar technology shows substantial cost decrease while wind did not
- Unit construction cost of CCGT was the lowest while that of solar was the highest in average

	Coal	CCGT	Nuclear	Solar	Wind
Period	1984 - 2017	1992-2019	1978 - 2019	2005-2019	2004-2019
Learning rate	-2.23%	**-6.70%	-1.71%	***23.74%	-0.36%
R <sup>2</sup>	0.01	0.14	0.03	0.62	0.00
Mean (KRW/kW)	1,380,266	829,673	2,540,236	4,535,774	2,584,806
Standard deviation	330,892	156,964	402,651	3,540,212	716,829

< Learning rate of each technology >

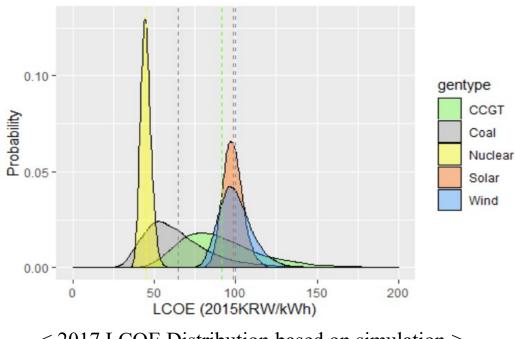
- Distribution of key parameters
  - Market factor: derive probability distribution based on historical data\*
  - Technology factor: Learning rate
  - Policy factor: Optimal carbon price escalation rate (Peck & Wan, 1996)\*\*

		Conventional			Renewable		
	-	Coal	CCGT	Nuclear	Solar	Wind	
	Life time (years)	40	30	40	25	25	
Market	Fuel Import Price	Probability distribution			N/A		
factor	Capacity Factor	Probability distribution					
	Interest rate	4.5%					
	Thermal Efficiency	Historical maximum			N/A		
Technology	Construction cost	Learning rate & Uniform distribution within a 95% confidence interval					
factor	Construction cost						
	Specific O&M cost	Fixed at the most recent			nt value		
Policy	Carbon Price	Probability distribution					
factor							

\* We derive distribution using AD test, Shapiro-Wilcox test, and Kolmogorov-Smirnov test to derive probabilistic distribution

\*\* Carbon price distribution was also derived from the ETS market price with assumed 7% cost escalation in (Peck & Wan, 1996).

- Monte Carlo Simulation
  - Pair-wise comparison of 10,000 Monte Carlo simulated samples
  - <u>Cost reversal probability</u> (CRP) reveals the probability of one technology become cheaper than the other technology
    ex) CRP (Coal, CCGT) = 18.8% CRP (Coal, Solar) = 7.6%

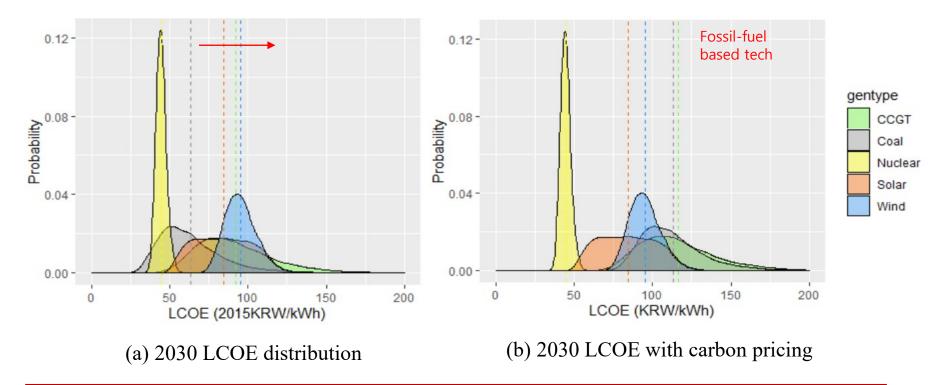


Energy Transition

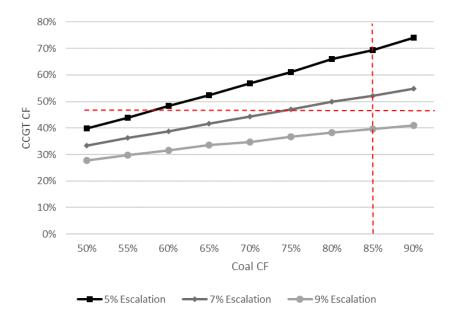
- Without policy intervention, solar will become cheaper than CCGT, but remain relatively expensive compared to baseload technology

→ CRP (Coal, Solar) = 20.7% CRP (Coal, Wind) = 9.2%

- Carbon pricing will relatively make renewables more cost competitive.
- → CRP (Coal, Solar) = 85.2% CRP (Coal, Wind) = 77.6%



- Coal to Gas switching
  - Another strategy to reduce carbon intensity of the energy system
  - If coal keeps current capacity factor (85%), slight increase in CF of CCGT above 50% will make CCGT cost competitive
  - <u>Combination of carbon pricing and increase use of CCGT can phase-out the</u> <u>coal power</u>



< Capacity factor of Coal and CCGT when order change probability is same >

\* Dashed line shows the capacity factor of coal and CCGT in 2017, which is 48%

# (6) Conclusion

- The change in LCOE of fossil-fuel based power has been accounted for mainly by <u>shifting fuel import prices</u>, while that of nuclear power has been driven primarily by <u>O&M costs</u>.
- No policy measure on the table would keep coal power plants costcompetitive. <u>Carbon pricing is pivotal</u> to accelerate the nation's lowcarbon energy transition.
- Transition away from fossil fuel-based power generation decrease the sector's reliance on imported fuel, <u>reducing the overall volatility of</u> <u>power generation cost and promoting the nation's energy security</u>.
- Limitations: We did not consider the <u>potential multivariate relationship</u> between cost parameters and additional <u>system-level costs</u> of renewables arising from the intermittency. Future research would investigate the contribution of these effects

#### References

- Aldersey-Williams, J., & Rubert, T. (2019). Levelised cost of energy–A theoretical justification and critical assessment. Energy policy, 124, 169-179.
- Buchholz, K. (June 20, 2019). Korea's Ambitious Plan to Grow Renewables [Digital image]. Retrieved June 06, 2021, from https://www.statista.com/chart/18454/electricity-generation-in-korea-by-type/
- Boccard, N. (2014). The cost of nuclear electricity: France after Fukushima. *Energy Policy*, *66*, 450-461.
- Lucheroni, C., & Mari, C. (2017). CO2 volatility impact on energy portfolio choice: A fully stochastic LCOE theory analysis. Applied Energy, 190, 278-290.
- Peck, S. C., & Wan, Y. S. (1996). Analytic solutions of simple optimal greenhouse gas emission models. In Economics of atmospheric pollution (pp. 113-121). Springer, Berlin, Heidelberg.
- Grubler, A. (2010). The costs of the French nuclear scale-up: A case of negative learning by doing. *Energy Policy*, *38*(9), 5174-5188.
- Geissmann, T., & Ponta, O. (2017). A probabilistic approach to the computation of the levelized cost of electricity. Energy, 124, 372-381.
- Heck, N., Smith, C., & Hittinger, E. (2016). A Monte Carlo approach to integrating uncertainty into the levelized cost of electricity. *The Electricity Journal*, *29*(3), 21-30.
- Koomey, J., & Hultman, N. E. (2007). A reactor-level analysis of busbar costs for US nuclear plants, 1970–2005. *Energy Policy*, *35*(11), 5630-5642.
- McNerney, J., Farmer, J. D., & Trancik, J. E. (2011). Historical costs of coal-fired electricity and implications for the future. *Energy Policy*, *39*(6), 3042-3054.