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Sustainability at the Crossroads:
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for a Sustainable Economy

Power Sector Asset Networks: Determinants of the Diffusion of Renewables

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Abstract

The simultaneous expansion and decarbonisation of the global power sector is imperative for achieving the mutually dependent goals of poverty alleviation and the mitigation of climate change. Substantial policy and cost reductions in renewable generating options over the period of 2007 to 2017 were met with a three-fold increase in global renewable generating capacity. If sufficient renewable generating capacity is to be deployed to meet sustainable development goals, early evidence of the dynamics thereof might be captured in this period.

Asset-level data sets of the global power sector have been obtained from S&P Market Intelligence for the years 2007 through 2017. Power sector assets, companies, and countries are arranged into a series of bipartite social networks for three fuel classes: fossil fueled generation, low-carbon (nuclear and hydro) generation, and renewable generation. Bipartite networks are projected on both company are country nodes to create directed networks. Basic network properties are analysed over time to reveal basic trends in the emergence of renewable generating options. The network analysis confirms that the ongoing energy transition is one of paradigmatic insurgency rather than steady evolution. Renewable generating companies are smaller and operate in more countries than incumbent fossil fuel and low-carbon competitors. The country projection is analysed using a fixed effect model to identify peer effects on the adoption of renewable generating options. Peer effects on the adoption of renewable generating options given the fixed effect model as currently developed are found to be insignificant.

Results are discussed and ambitions for future work are articulated. This paper is under development as part of the Oxford Martin School Programme on the Transition to a Post-Carbon Economy.

1. Introduction

The defining challenge of the 21st century is the dual imperative of eliminating global poverty while constraining climate change to safe levels (Stern 2015). Meeting the goals of the Paris Agreement will require the complete descarbonisation of the energy system. Many cost-efficient paths to mitigating global climate change require that the power sector lead the transition of the energy system, with most (IPCC 2014). The pathways also involve the substantial growth of the power sector, as the portion of energy services met with electricity increases, particularly transport and heat (e.g. IPCC 2014, IEA 2017, ETC 2017). Further, electrification is an urgent development priority, providing an input commodity for a wide range of other economic activities, and being directly required for a number of development indicators like healthcare, education, water supply, and sanitation. Catastrophic climate change will disporportionately affect the global south (e.g. Mercer 2015), meaning it is only possible address development and sustainability priorities simultaneously. The simultaneous expansion and decarbonisation of the global electricity system is an urgent priority.

Between 2007 and 2017 generating capacity of grid-scale (>1MW) solar photovoltaic, wind, and bio-energy (‘renewables’) increased from 484GW to 1,442GW – 6.5\% and12\% of total generating capacity respectively. Over this period, the module cost of solar PV power fell from $1.3/W to less than $0.6/W, wind turbine costs fell from €1.32/W to €0.89W, and Lithium Ion battery pack costs fell from over $1000/kWh in 2010 to less than $209/kWh in 2017 (BNEF 2016, 2017). The Kyoto Protocol entered into effect, the Paris Agreement was signed, and the portion of all carbon emissions which were priced went from 5\% to 1% (World Bank 2017). The International Energy Agency (IEA) projects that to achieve a sustainable development pathway that meets the development needs of the global South while constraining warming to less than 2^{o}C, the installed capacity of renewables must increase to 6,664GW and 51\% of all generating capacity by 2040 (IEA 2017a). If this fourteen-fold increase is indeed occurring, early evidence might be seen in this time period.

The IEA, arguably the publisher-of-record for global energy system statistics and projections, has been criticized for systematically underestimating changes in the energy system, particularly changes in the price and diffusion of renewable generating options (CTI 2017, De Vos & De Jager 2014). Projected changes in energy systems are contentious and subject to deeply entrenched interests - they are critical inputs for investment decisions (as in the controversial use of the IEA’s Current Policies Scenario by Peabody Energy (Attorney General of the State of New York 2015)), become flashpoints in corporate governance debates (such as in the advocacy of the Aiming for A coalition (Shareaction 2017)), and provide benchmarks for a range of policy and finance interventions (E.g. CDP’s science-based targets (2017), Oxford Martin School’s Working Principles for Investment in Fossil Fuels (2015), 2dII 2^{o} portfolios (2015)).

The IEA employs equilibrium models in their projections which seek to balance energy demand with investment in supply (IEA 2017a)(see e.g. Pindyck 2013 for a review). These models generally conform to linear models combining research, development, and policy ‘push’ (Jensen et al. 2007) with demand ‘pull’ (Godin 2013, 2015). They are less capable of interrogating techno-economic path dependence (Geels 2002, Martin 2006), the (un)embeddedness of information and institutions (Binz et al 2014, Chaminade 2015), the mission-alignment of renewable energy innovation (Mazzucato 2015), and the grain size of energy system capital goods. The socio-technical nature of innovation (see Rip & Kemp 1998) in the global energy system lends itself to social network analysis where peer effect itself can be causal (Moffit 2001) without intervening utility functions and price formation.

The goal of this paper is to be able to identify *sensitive intervention points* and *tipping* points in the transition to a post-carbon economy. A sensitive intervention point is where a small adjustment of one or more control variables can deliver a significant change in an import state variable (Farmer & Hepburn 2017). Understanding the global power sector as a social network of assets, companies, and countries may help identify these points and builds towards an economic model of climate change suited for purpose (see Farmer et al (2015) for a critique of current models). It is being prepared as part of the Oxford Martin Programme on the Transition to a Post-Carbon Economy.

Section 2 reviews the use of social networks to study technology diffusion, and their application to innovation and learning - particular in the context of energy systems. Section 3 describes data sources and preparation. Section 4 describes network formation and indicative attributes. Section 5 presents a fixed-affect model to determine peer diffusion affects. Section 6 presents early work on more sophisticated diffusion models. Section 7 concludes.

2. Networked Diffusion, Learning, and Innovation

Networks comprised of decision-makers and their social relationships have proven useful for understanding the significance of peer and network effects in a wide range of problems. Policy makers and marketers alike seek models to describe how technologies (in the broadest sense) might diffuse through a population of decision-making agents, for either the purposes of designing policy interventions (see, e.g. Athey 2017) or successfully marketing a product (e.g. Bloom 2013). The canonical Bass model (1969) and its derivatives (e.g. Mahajan et al. 1990) explain how technology is adopted via social contagion, reproducing sigmoidal trends observed across industries and time periods (E.g. Griliches 1957, Rogers 1962, 1983, Blackrock 2015).

Network effects capture a range of incentives for networked decision-makers and may be either direct or indirect (see, e.g. Birke 2009). Direct effects capture the increase in utility proportional to the network degree - such as by the socialisation of costs on for telecommunications or sanitation infrastructure, or the coordination to a common industry standard or social protocol such as driving on the left or right. Indirect network effects are of greater interest to this study: the benefits to technology adopters based on informational spillovers, learning effects, and uncertainty reduction (Katz & Shapiro 1986), bearing many similarities to evolutionary economic geography (Martin 2006). Peer effects (see Moffit 2001) offer a more broad definition in the identification of causal influence between an agent's actions and those of its peers.

Allan et al. (2014) have surveyed the diffusion of renewable energy technologies. Social networks have been commonly applied in the study of energy technology adoption decisions by households. Examples include the diffusion of smart meters in the UK (Cassidy 2015), solar photovoltaics in Germany (Darshing 2017) and California (Bollinger 2012), biogas generation in China (He 2015). These social network studies use the geospatial locations of technology deployments to study the diffusion of technology along edges derived from geospatial proximity. Vega & Mandel (2018) use a network of wind turbine installations to examine the diffusion of wind power.

3. Data Preparation and Network Formation

3.1 Data Description

Asset-level data for the global power sector have been obtained from S&P Market Intelligence's World Electric Power Plant database (WEPP) for the years 2007 through 2017 inclusive. WEPP is a feature-rich database of power generating units, their locations and parameters, and their corporate owners, see Table A1. WEPP's authors claim complete overage (>95%) for almost all fuel and conversion technologies over 50MW in size, comprehensive (>75%) coverage for smaller generating units or select conversions and geographies, particularly China, and less than comprehensive coverage (<75%) for only a few niche technologies or geographies (IEA 2017b). Fuel classes have been aggregated into three characteristic categories, fossil fuels, low-carbon, and renewables, according to Table A2. Hydro Power has been included in the ‘low carbon’ fuel class because the power stations are typically large, fixed capital assets, and in many countries in the world the economic hydropower resources have been fully realised. Regional definitions are adapted from the regional definitions of the IEA World Energy Outlook series of publications, see Table A3.

Figure 1 shows the growth of global generating capacity by fuel class and company size. Select regions are shown in Figures A1a through A1h. All regions have large single companies with dominant market positions and almost exclusively fossil fuel or low-carbon generating options. These large incumbent companies are often government ministries or regulated monopolies, or the same reborn as post-liberalisation national champions. In many regions there is a rapid adoption of renewable generating option underway. The companies adopting renewables are often much smaller and numerous than incumbent fossil or low-carbon generating companies. The growth of generating capacity in the global south is also immediately apparent. Aggregate statistics for the sample period data are shown in Table 1.

[Figure 1: Global Cumulative Generating Capacity]

[Table 1: Aggregate Data from Sample Period]

3.2 Network Formation

The location of assets is used to organise the panel data into a bipartite network of companies and countries. Location data is commonly used in the construction of unobserved social networks - positing that by geospatial proximity alone two nodes are more likely to have a social relationship. Company and country nodes are connected by edges weighted according to the generating capacity of company assets located in the given country. This network formulation creates a bipartite graph, wherein no two countries or companies are joined by an edge. The bipartite network graph is developed in Equations 1 to 6.

$$\textit{Let undirected bipartite graph } G=G(U,V,E) \textit{ with:} \tag{1}$$

$$\textit{Nodes} \quad U = \{country_1 \ldots country_r\} \tag{2}$$

$$V = \{company_1 \ldots company_s\} \tag{3}$$

$$\textit{Edges} \quad E = \{(u, v) = \textstyle\sum asset_{MW} \,|_{asset_{country}=u, asset_{compay}=v} \;\forall\; u \text{ in } U, v \text{ in } V\} \tag{4}$$

$$\textit{Biadjacency Matrix} \quad B = \begin{bmatrix} b_{0,0} & \cdots & b_{r,0} \\ \vdots & & \vdots \\ b_{0,s} & \ldots & b_{r,s} \end{bmatrix} \forall\; b \text{ in } E \tag{5}$$

$$\textit{Adjacency Matrix} \quad A = \begin{pmatrix} 0_{r,r} & B \\ B^T & 0_{s,s} \end{pmatrix} \tag{6}$$

Three graphs are prepared for the three aggregate fuel classes: G_G for renewables, G_B for low-carbon generation, and G_F for fossil fuel generation. For each fuel class, the subset of the company’s assets belonging to each fuel class are considered the assets of that company – a company can appear in the node set V of all three graphs.

3.3 Bipartite Network Analysis

The simple degree of a node in an undirected graph may be calculated according to Equation 7.

$$Degree \quad d_i = \sum_j \begin{pmatrix} a_{i,j} > 0 = 1 \\ else = 0 \end{pmatrix} \forall\, a \; in \; A \qquad 7$$

Graph degree distributions provide early insight into the determinants of the formation of random graphs. Degree distribution means have been prepared for company nodes *V* in the bipartite graphs G_G, G_B, *and* G_F, see Figure 2.

[Figure 2: Mean Company Degree Distributions]

Between 2007 and 2017 mean degree distributions for company nodes *V* in G_G and G_B increased. Power generating companies were in general more likely to have renewable and low-carbon assets in multiple countries in 2017 than they were in 2007. Degree distributions for companies with renewable power assets showed the most pronounced increase and have mean degrees much higher than fossil fuel and low-carbon generating companies. Degree distribution means in all three graphs are quite low – the multiplicity of small companies operating in a single country reduces the mean degree substantially. Figure 3 is more illustrative.

[Figure 3: Degree Distributions for all Companies]

In general, very few companies operate low-carbon generating assets in multiple countries. Between 2007 and 2017 the number and degree of companies operating renewable and fossil fuel assets in multiple countries substantially increased. The largest fossil fuel and low-carbon generating companies only have assets in a single country. Companies with renewable generating assets, even large ones, are more likely to have assets in more countries.

The degree distributions for country nodes U in the bipartite graphs G_G, G_B, *and* G_F have been color-coded according to the country's region, see Figure 4 and 5. The mean degrees for renewable and fossil fuel portions of countries *U* have increased substantially since 2007. India, in particular, has a high degree rivalling that of the United States for renewables generation. China has a small degree across all fuel classes relative other countries of similar size.

[Figure 4: Mean Company Degree Distributions]

[Figure 5: Degree Distributions for all Companies]

4. Network Projections

An undirected bipartite graph *G(U,V,E)* can be projected to row-stochastic directed graphs *G'(U,E')* and *G'(V,E')* for the purposes of identifying peer effects among either the node sets *U* or *V.* Equations 7 through 10 describe the

Let directed row-stochastic $G'_U = G'(U,E')$ *with:* 8

$$Adjacency\ Matrix \quad A'_U = \|A\|.\|A^T\| \qquad 9$$

Let directed row-stochastic $G'_V = G'(V,E')$ *with:* 10

$$Adjacency\ Matrix \quad A'_V = \|A^T\|.\|A\| \qquad 11$$

Both the country- and company-projections seek to identify peer effects which are not strictly observed. Such peer effects might arise from geospatial proximity, an analogous social network of individuals (in a labour supply, consultants, etc), or a local supply chain.

4.1 Company Projection

The company projection uses country co-location to determine social relationships between companies. Network edges signify that two companies share common exposure to policies, labour, and markets conditions across countries. Snapshots of the company projection are shown in Figure 6 using a force-directed layout and seeding node positions according to the centroid of the country wherein lies the plurality of the company's assets.

[Figure 6: Company Projection]

4.2 Country Projection

The country projection uses company ownership of co-located assets to determine social relationships between countries. Network edges signify that two countries have companies with assets in both countries. Snapshots of the country projection are shown in Figure 7 using the country centroids as node positions.

[Figure 7: Country Projections]

Three country-projected networks have been prepared for the three aggregate fuel classes: $G'_{U,B}$, $G'_{U,G}$, $G'_{U,F}$. Select network properties have been analysed for the three networks and are shown in Figure 8. Snapshots of the major component of the three networks are shown in Figure 9.

[Figure 8: Network properties of $G'_{U,G}$, $G'_{U,B}$, and $G'_{U,F}$]

[Figure 9: Major Component in $G'_{U,G}$, $G'_{U,B}$, and $G'_{U,F}$]

All three network projections increased in number and size of components over the period while decreasing in isolated nodes. $G'_{U,G}$ and $G'_{U,F}$ feature single large major components. The major component of $G'_{U,F}$ had a degree of about 6 through the study period, while the degree of the major component of $G'_{U,G}$ continued to grow.

Assortativity is the preference of nodes to form links with other nodes according to some property. Figure 8 shows the assortativity of nodes in $G'_{U,G}$, $G'_{U,B}$, and $G'_{U,F}$ according to the region attribute of the nodes. Countries in the region OECD_EUR are assortative with themselves across all three fuel classes and the entire study period. Assortativity in low carbon generation seems likely driven by geospatial proximity of the regions – OECD_EUR with itself and TE through the whole study period, and AFRICA and LAM emerging as self-assortative regions by 2017. Assortativity in $G'_{U,G}$ reduced over the study period while OECD_EUR maintained a central role with the other regions.   Assortivity increased in $G'_{U,F}$ as AFRICA and LAM developed mutual preferences for themselves and each other.

[Figure 10: Assortativity for Region Attribute]

5. Fixed-Effect Model

In order to demonstrate causality in peer effects (per Moffit 2001), a model must be constructed which controls for self-selection (homophily), correlated unobservables, and simultaneity. A fixed-effect model is prepared as in Bollinger (2012) and Ke (2016). The fixed effect model seeks to identify peer effects in the diffusion of the portion of renewable generating capacity in nodes in G'_U. The model uses the previous year's inbound influences to test whether they are detrimental in the given year's renewable generating capacity.

5.1. Model Preparation

The portion of renewable generating capacity is given by Equation 12. Inbound influence on that node is given by Equation 13. A Fixed Effect Model is then prepared as in Equation 14. Returning to Moffit's (2001) conditions for causality in peer effects, the model used must control for simultaneity, homophily, and correlated unobservables.

This model formulation uses a one-hot vectorisation of countries so that all attributes or parameters that might be associated a given country are captured by that country's unique regressor. This avoids homophily as no two countries have the same type. Per Bollinger (2012) and Ke (2016), simultaneity of agent actions can be controlled for by using only past actions of an agent's neighbours in determining peer effect. This is done by only considering the inbound peer influence on a given agent from the previous time step. Correlated unobservables are not controlled in this model. Typical approaches use either an instrumental variable analysis (as in Ke 2016) or a difference-of-differences approach (as in Bollinger 2012, Bloom 2013) to control for correlated unobservables. Finally, the date is appended to the independent data and they are concatenated together to give a dataframe of the form in Equation 15.

With biadjacency matrices B and B_G:

Renewable Portion $$POR\_GREEN_i = \sum_j \frac{b_{G,i,j}}{b_{i,j}} \ \forall \ i \ in \ \{0 \ldots r\} \qquad 12$$

Inbound Influence $$INFLUENCE = A'_U . POR\_GREEN \qquad 13$$

Fixed Effect Model $$POR\_GREEN_{i,t} = \beta_0 INFLUENCE_{t-1} + \alpha_i + \gamma_t + \varepsilon \qquad 14$$

With: β_0 *as a time- and country-fixed coefficient of peer influence*

α_i *as a time-fixed coefficient for country i (one-hot breakout)*

γ_t *as a universal time coefficient*

ε *as an independent and identically distributed random variable*

DataFrame $$Y[POR\_GREEN] \sim X[INFLUENCE_{t-1}, DATE, \{AD, \ldots, ZW\}, Constant] \qquad 15$$

5.2 Least-Squares Minimisation

A least-squares minimisation is applied to the dataframe in Equation 15 to obtain the parameters β, γ, α_i, and ε. The parameter coefficients and t-statistics are shown in Figure 9.

[Figure 11: Fixed Effect Model Coefficients and T-Statistics]

The country dependent parameters α_i range from slightly negative to highly positive. In certain regions, like OECD_EUR, ME, and OECD_AMX, countries show a positive affinity for adopting renewables, all other things being equal. In others, like TE, AFRICA, and OTHERX, country parameters indicate a reluctance to adopt renewables. The time-dependent parameter γ and constant parameter ε are approximately an order of magnitude smaller than the country parameters α_i. Both, however, are positive and significant to the model. The peer-influence parameter β does not meet the critical t-statistic for the model.

6. Discussion and Next Steps

6.1 Discussion of Findings

Analysis of the topology and evolution of the networks examined above provide useful narratives about the changes in the power sector. The global power sector is undergoing globalisation, with more companies operating assets in multiple companies over the time period. Renewable power generation is growing rapidly in some regions and countries, and not at all in others.

The size and degree of companies building renewable generating options are substantially different to the size and degree of companies building fossil fuel or low-carbon generating options. The former are emerging with small numbers of assets and small aggregate generating capacities. They are more likely to operate assets in multiple countries relative to companies with fossil fuel and low-carbon assets. Many of the companies with fossil fuel and low-carbon generating capacities are large incumbents, often vertically-integrated state-run generating companies. Regional groups of countries show some homophily - companies own and operate assets with a bias to certain regional groups.

The basic fixed-effect model prepared and presented here offers less useful insight. Peer effect, the phenomena of interest, barely appears to impact the amount of renewable generating capacity being built in countries. This model does not account of correlated unobservables and has only been applied on the country-projected graph G'_U.

6.2 Pending Work and Improvements

The fixed effect model presented in this paper needs to be revisited. The properties of this model which satisfy the causality of peer effect need to be better articulated and documented. The bipartite graph and its projections are not immediately analogous to the use of the fixed effect models in the referenced papers. This difference needs to be interrogated.

Additional attributes for country nodes which may be correlated with renewable power deployment may add resolution to the fixed effect model and reduce the dominance of the country parameters. A number of attributes are available as simple datasets: carbon pricing coverage (from, e.g. the World Bank 2017), renewable energy subsidies scheme (from, e.g. REN21), power market concentration, and power market structure (i.e. extent of liberalisation, etc.). Some attributes may be themselves be better arranged as a network, for example geographic adjacency. Diffusion can be measured across these multilayer networks as in ref ().

Advanced diffusion models use more sophisticated measures of centrality (e.g. Eigenvalue centrality, PageRank). The calculation of these centrality measures and their adoption in a more sophisticated diffusion model may better illuminate the relationships between assets, company strategies, and country-level policies.

7. Conclusion

The global power sector is rapidly expanding, particularly in the Global South. An insurgence of renewable generating capacity is disrupting large fossil fuel and low-carbon incumbents.

The companies with renewable generating assets are typically smaller than fossil fuel and low-carbon incumbents and are regionally concentrated. Using asset-level data from S&P Market Intelligence company and country asset aggregations are arranged into a bipartite network. The bipartite network is also projected to networks of only country- and company-nodes.

Network properties are analysed over time for renewable, low-carbon, and fossil fuel classes. Network properties reveal the rapid deployment of renewables and that companies and countries with renewable generating capacity are much more connected than fossil fuel and low-carbon counterparts. Some regional homophily is observed.

A fixed effect model is used to identify peer effects on the adoption of renewable generating options. Peer effects are found to be insignificant relative to country, date, and constant regressors. The peer effect model developed in this study has extensive potential for improvement. Future plans for this work also include the introduction of extensive complementary policy datasets and and exploration of other model types to better identify the primary drivers of renewable generating technology.

Tables and Figures

Figure 1: Global Cumulative Generating Capacity

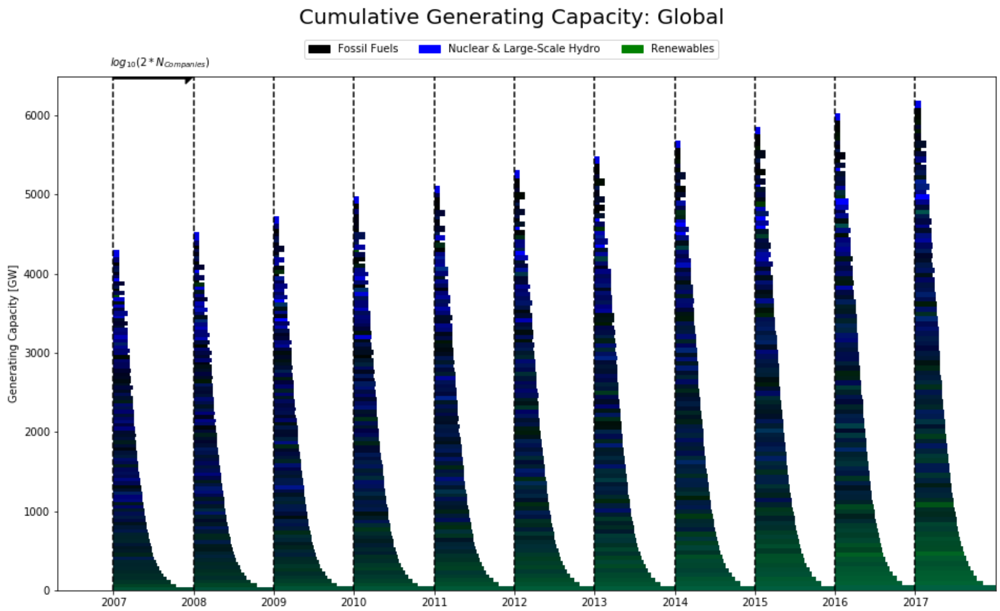


Figure 2: Mean Company Degree Distributions

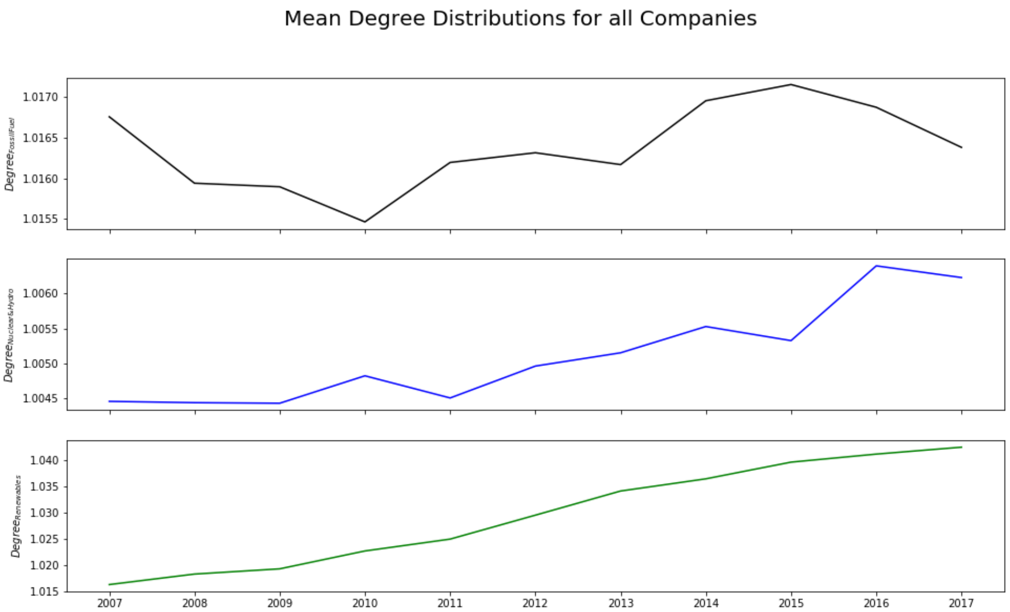


Figure 3: Degree Distributions for all Companies

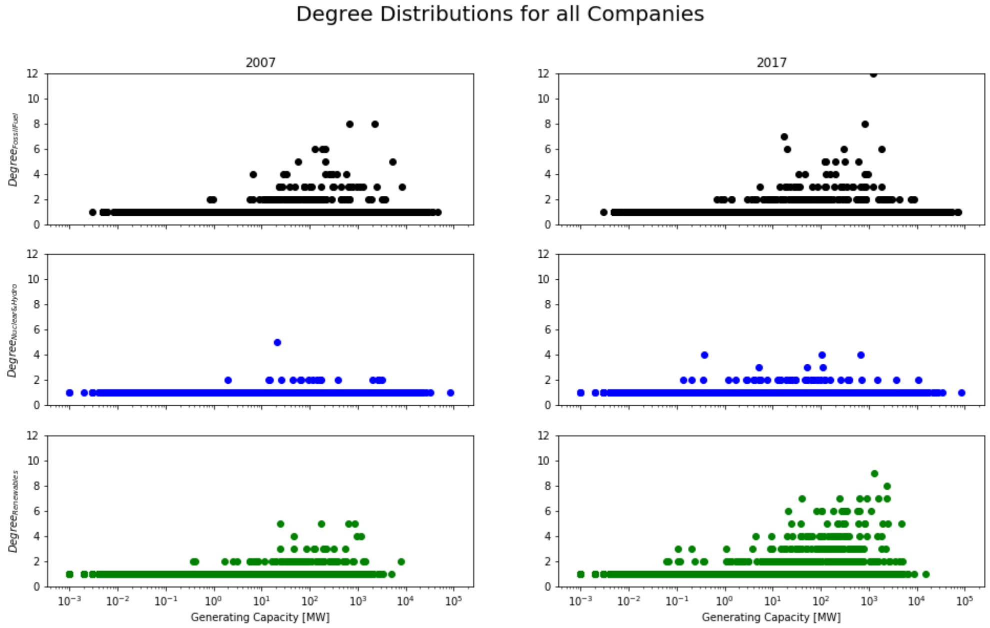


Figure 4: Mean Country Degree Distributions

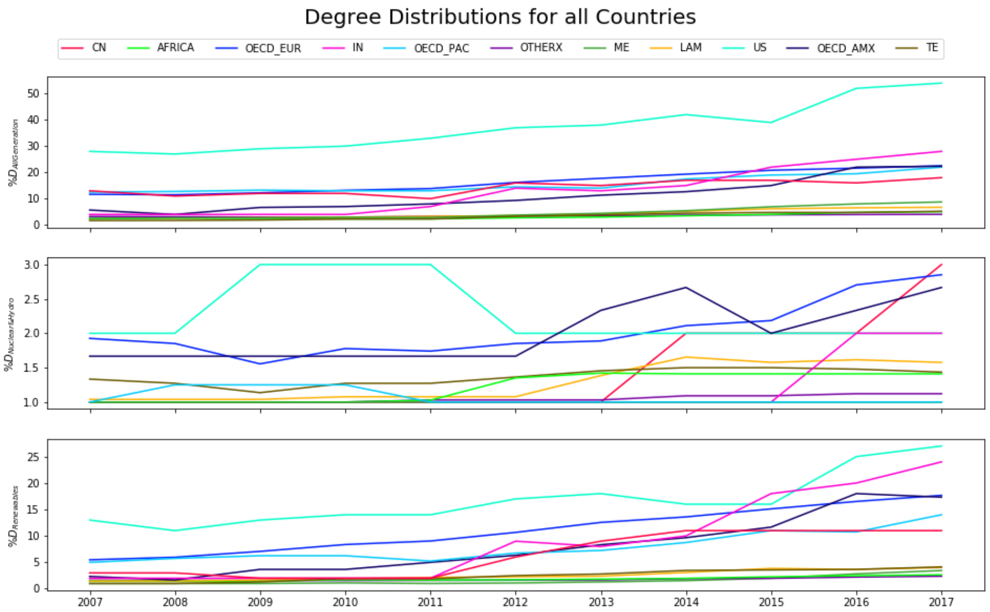


Figure 5: Degree Distributions for all Countries

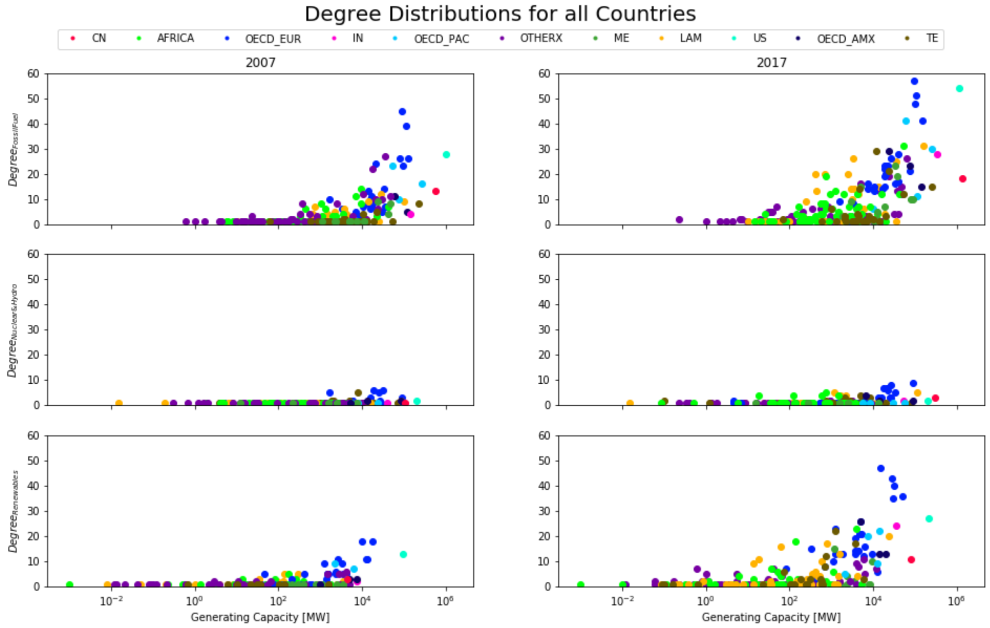


Figure 6: Company Projection

2007 **2017**

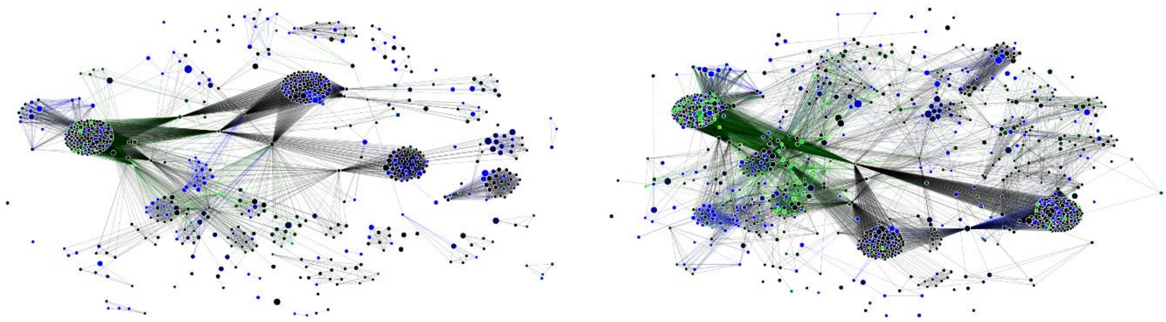


Figure 7: Country Projection

2007 **2017**

G'$_{U,F}$

$G'_{U,B}$

$G'_{U,G}$

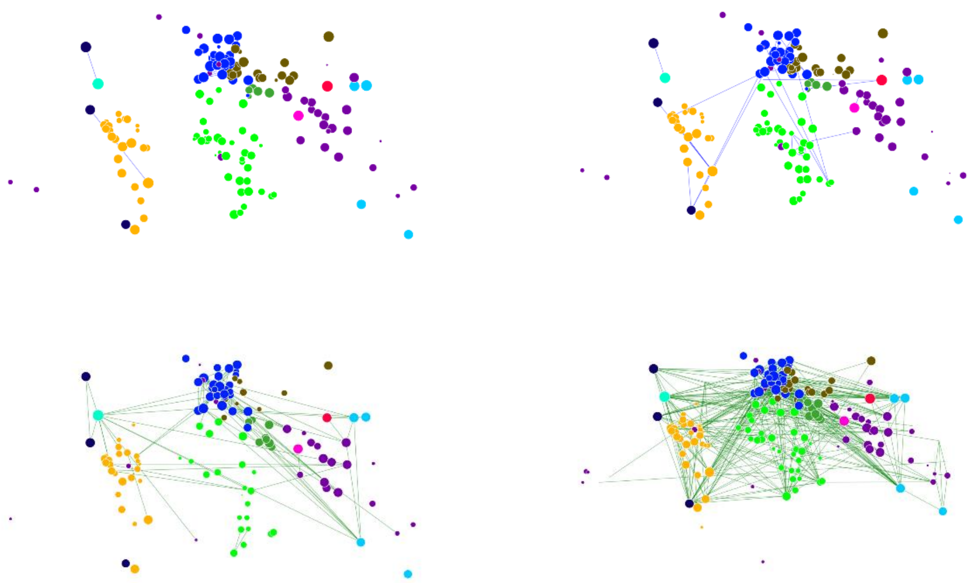


Figure 8: Network properties of $G'_{U,B}$, $G'_{U,G}$, and $G'_{U,F}$

$G'_{U,F}$

$G'_{U,B}$

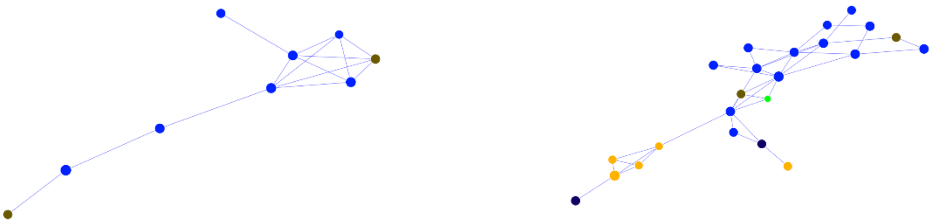
$G'_{U,G}$

Figure 9: Major Component in $G'_{U,B}$, $G'_{U,G}$, and $G'_{U,F}$

2007 **2017**

$G'_{U,F}$

$G'_{U,B}$

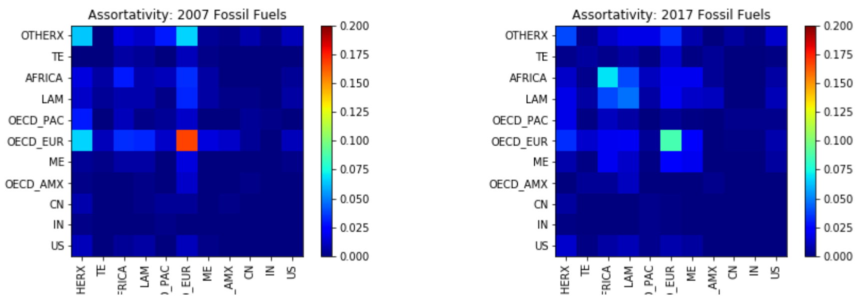


$G'_{U,G}$

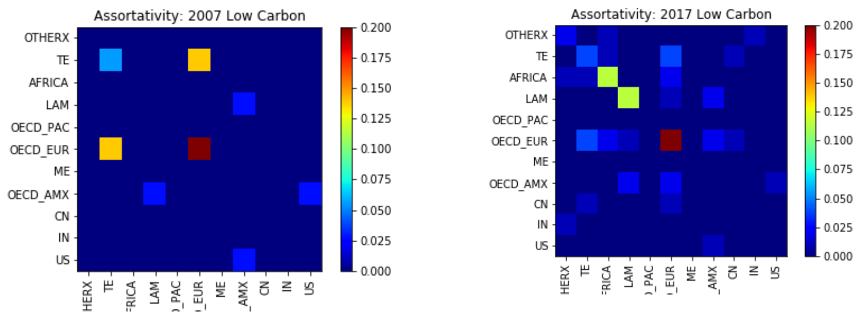
Figure 10: Assortativity for Region Attribute

2007 **2017**

$G'_{U,F}$



$G'_{U,B}$



$G'_{U,G}$

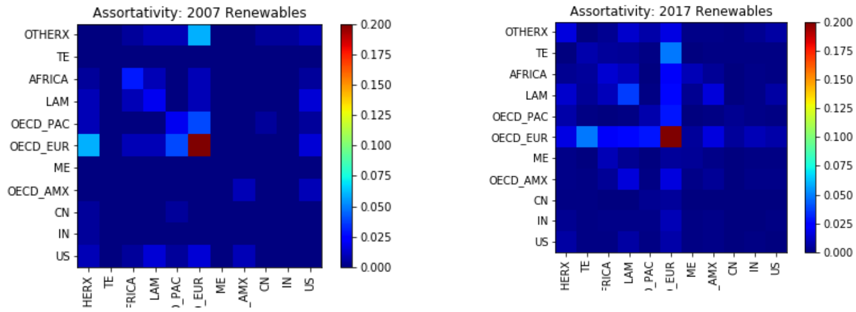


Figure 11: Fixed Effect Model Coefficients and T-Statistics

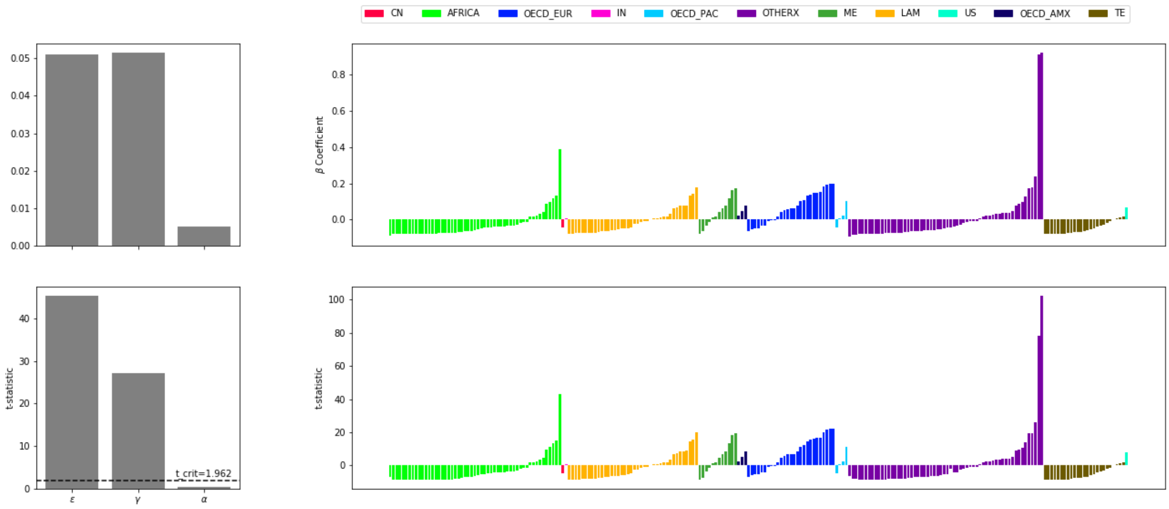


Table 1: Aggregate Data from Sample Period

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Plant (how many) - company (how many) - countries (how many) .

Fuel - what type (how many)

table - aggregates, average degree - company; average degree - country

\\

References

2°II (2015), *Assessing the Alignment of Portfolios with Climate Goals.*

Allen, C., Jaffe, A. B., & Sin, I. (2014) 'Diffusion of Green Technology: A Survey', *Working Paper 14_04,* Motu Economic and Public Policy Research.

Athey, S., & Imben, G.W. (2017), 'The State of Applied Econometrics: Causality and Policy Evaluation', *Journal of Economic Perspectives*, 31(2): 3-32.

Attorney General of the State of New York (2015), *Assurance of Discontinuance, Assurance No. 15-242.*

Bass, F. (1969) 'A new product growth model for consumer durables', *Management Science.*

Bloom N., Schankerman, M., & Van Reenen, J. (2013), 'Identifying Technology Spillovers and Product Market Rivalry', *Econometrica*, 81(4): 1347-1393.

BNEF (2018), 'Tumbling Costs for Wind, Solar, Batteries are Squeeing Fossil Fuels', available at: https://about.bnef.com/blog/tumbling-costs-wind-solar-batteries-squeezing-fossil-fuels/.

BNEF (2016), *New Energy Outlook 2016.*

Binz, C., Truffler, B., & Coenen, L. (2014), 'Why spae matters in technology innovation systems – mapping global knowledge dynamics of membrane bioreactor technology', *Research Policy*, 43: 1-42.

Birke, D. (2009), 'The Economics of Networks: A survey of empirical literature', *Journal of Economic Surveys*, 23(4): 762-793.

Blackrock (2014), *Interpretting Innovation: Impact on Productivity, Inflastion, & Investing,* Blackrock Investment Institute.

Bollinger, B., & Gillingham, K. (2012), 'Peer Effects in the Diffusion of Solar Photovoltaic Panels', *Marketing Science*, 31(6): 900-912.

Carbon Tracker Initiative (2017), *Lost in Transition*

Cassidy, A. (2015), 'A Framework for Exploring Social Network and Personality-Based Predictors of Smith Grid Diffusion', *IEEE Transactions on Smart Grid*, 6(3): 1314-

CDP (2017), *Science-based Target Setting Manual.*

Chaminade, C. & Plechero, M. (2015), 'Do Regions Make a Difference? Regional Innovation Systems and the Global Innovation Networks in the ICT Industry', *European Planning Studies*, 23(2): 215-237.

Darshing, S, (2017), 'Household dynamics of technology adoption: A spatial econometric analysis of residential solar photovoltaic (PV) systems in Germany', *Energy Research & Social Science*, 23: 113-124.

De Vos, R. & de Jager, D. (2014), Energy Post, Available at: http://energypost.eu/world-energy-outlook-hides-real-potential-renewables/

Energy Transitions Commission (2017), N*ew electriciy era: How to decarbonise energy systems through electrification*.

Farmer, J. D. & Hepburn, C. (2017), *Tipping Points to the Post-Carbon Society*, public lecture given at the Oxford Martin School, 9 November 2018.

Farmer, J.D., Hepburn, C., Mealy, P., & Teytelboym, A. (2015), 'A Third Wave in the Economics of Climate Change', *Environmental Resource Economics*, 62: 329-357.

Geels, F.W. (2002), 'Technological transitions as evolutionary reconfiguration processes: a multi-level perspective and case study', *Research Policy*, 31(8-9): 1257-1274.

Grillches, Z. (1957), 'Hybrid Corn: An Exploration in the Economics of Technology Change', *Econometrica*, 25(4): 501-522.

Godin, B., & Lane, J.P. (2013), 'Pushes and Pull: History of the Demand Pull Model of Innovation', *Science, Technology, & Human Values,* 38(5): 621-654.

Godin, B. (2015), 'Models of Innovation: Why models of innovation are models, or what work is being done calling them models?', *Social Studies of Science*, 45(4): 570-596.

He, P. & Veronesi, M. (2015), 'The Diffuson of Information and Behavior in Social Networks: Renewable Energy Technology Adoption in Rural China', *Working Paper Series*, Department of Economics, University of Verona.

IEA (2017a), *World Energy Outlook 2017,* Paris, France.

IEA (2017b), *World Energy Model Documentation,* Paris, France.

IPCC (2014), *Climate Change 2014: Mitigation of Climate Change*, Working Group III Contribution to the Fifth Assessment Report, Cambridge University Press.

Jensen, M.B., Johnson, B., Lorenz, E., Lundwall, B. A. (2007) 'Forms of Knowledge and modes of innovation', *Research Policy,* 36: 680-693.

Katz, M. & Shapiro, C. (1986) 'Technology Adoption in the Presence of Network Externalities', *Journal of Political Economy,* 94(4):822-841.

Martin, R. & Sunley, P. (2006), 'Path dependence and regional economic evolution', *Journal of Economic Geography*, 6: 395-437.

Mahajan, V., Muller, E., & Bass, F.M. (1990), 'Diffusion of New Products: Empirical Generalisation and Managerial Uses', *Marketing Science*, 14(3): G79-G88.

Mazzucato, M. (2017), *Mission-Orientated Research & Innovation in the European Union*, European Commission.

Mercer (2015), *Investing in a Time of Climate Change*.

Moffit, R. (2001), 'Policy interventions, low-level equilibria, and social interactions', Durlauf SN, Young HP, eds. *Social Dynamics*, MIT Press, Boston, 45–82.

Pindyck, R. S. (2013), 'Climate Change Policy: What Do the Models Tell Us?', *NBER Working Paper No. 19244*, National Bureau of Economic Research.

REN21 (2017) *REN21 Global Status Report,* typical.

Rip, A., Kemp, R. P. M., & Kemp, R. (1998), 'Technological change', In S. Rayner, & E. L. Malone (Eds.), *Human choice and climate change. Vol. II, Resources and Technology* (pp. 327-399). Columbus, Ohio: Battelle Press.

Rogers, E. M. (1983), *Diffusion of Innovations*, The Free Press, New York, NY.

Shareaction (2017), *Two Years After 'Aiming for A': Where Are We Now?*

Standard & Poors (2017), *World Electric Power Plants Database*, S&P Market Intelligence, Typical.

Stern, N. (2015) *Why are we waiting?,* MIT Press.

Vega, S. H. & Mandel, A. (2018), 'Technology Diffusion and Climate Policy: A Network Approach and its Application to Wind Energy', *Ecological Economics*, 145:461-471.

The World Bank (2017), *Carbon Pricing Watch 2017.*

Appendix

Table A1: WEPP Features

Table A2: Fuel Classes Aggregation

Table A3: Regional Definitions

Figure A1a: Cumulative Generating Capacity, AFRICA

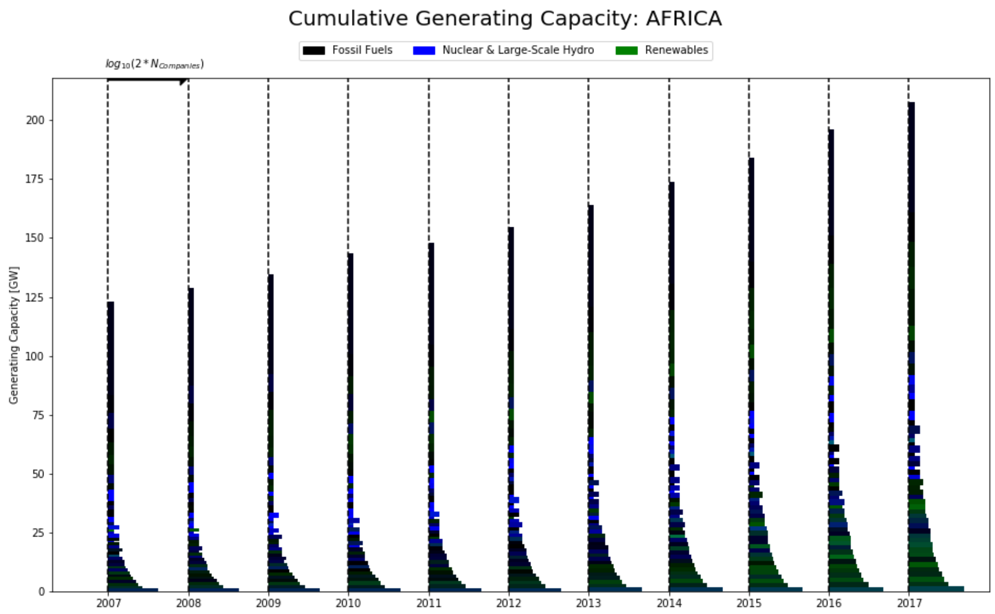

Figure A1b: Cumulative Generating Capacity, CN

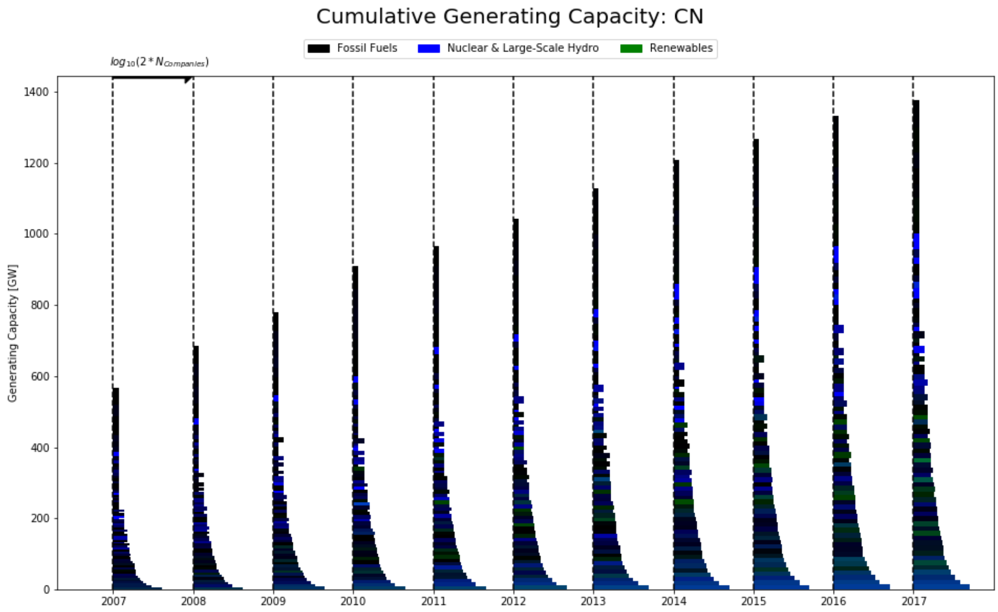

Figure A1c: Cumulative Generating Capacity, IN

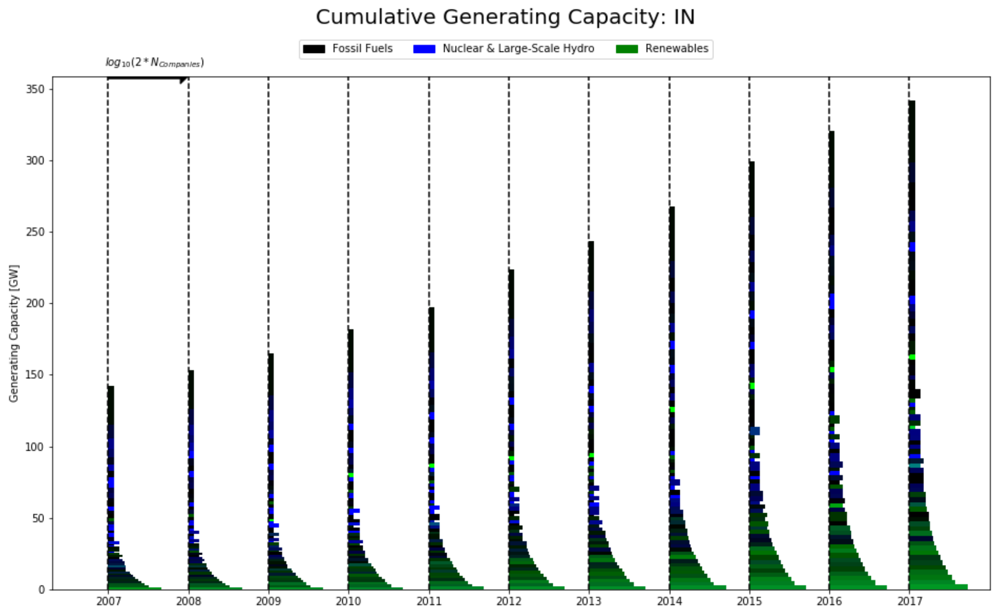

Figure A1d: Cumulative Generating Capacity, LAM

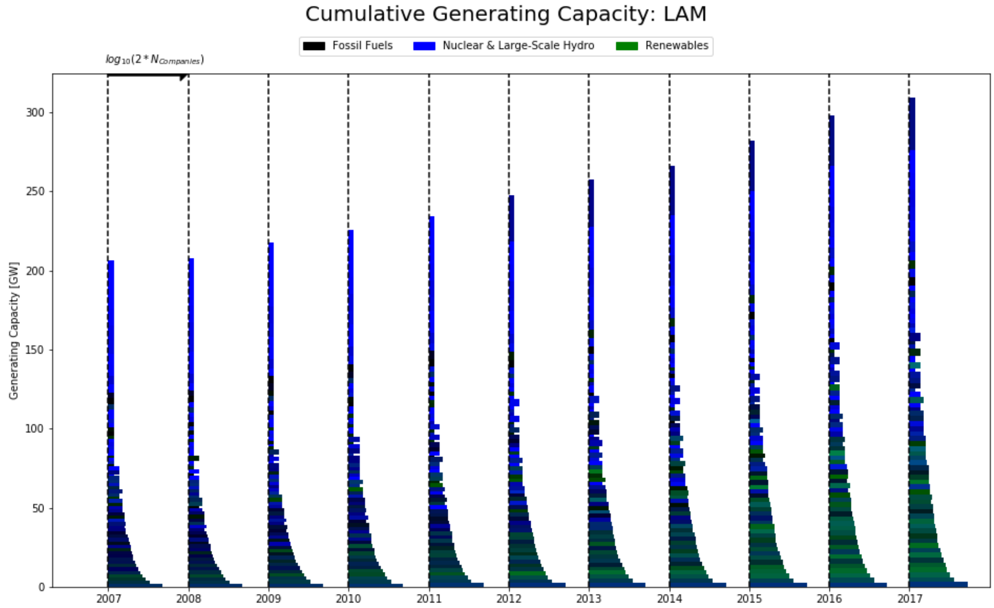

Figure A1e: Cumulative Generating Capacity, ME

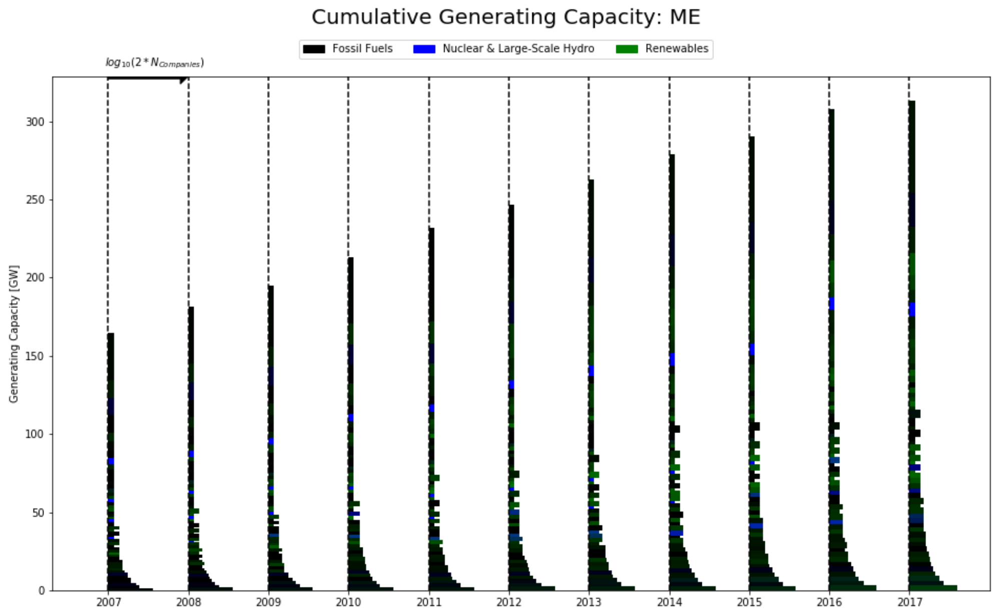

Figure A1f: Cumulative Generating Capacity, OECD_AMX

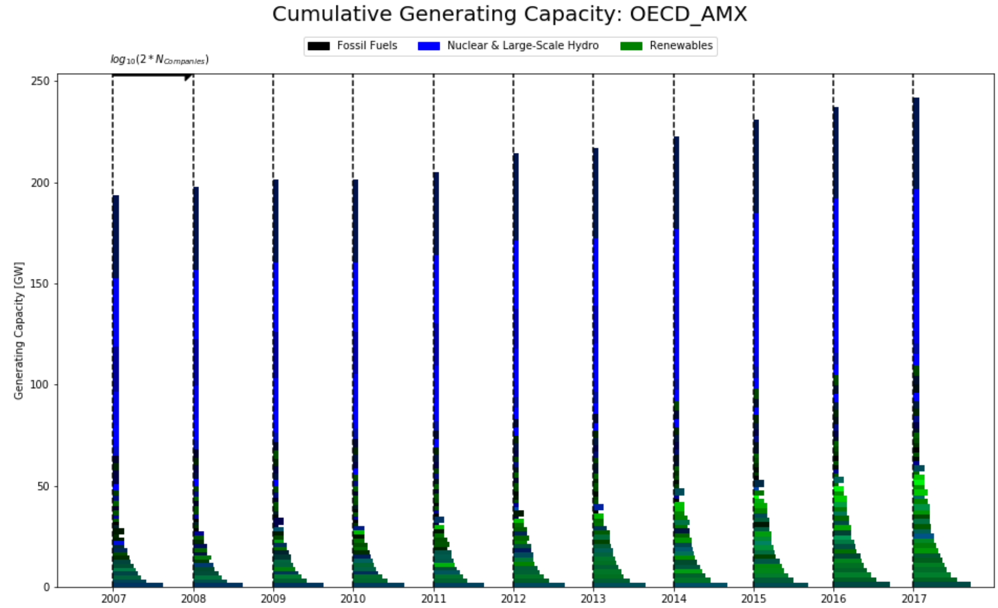

Figure A1g: Cumulative Generating Capacity, OECD_EUR

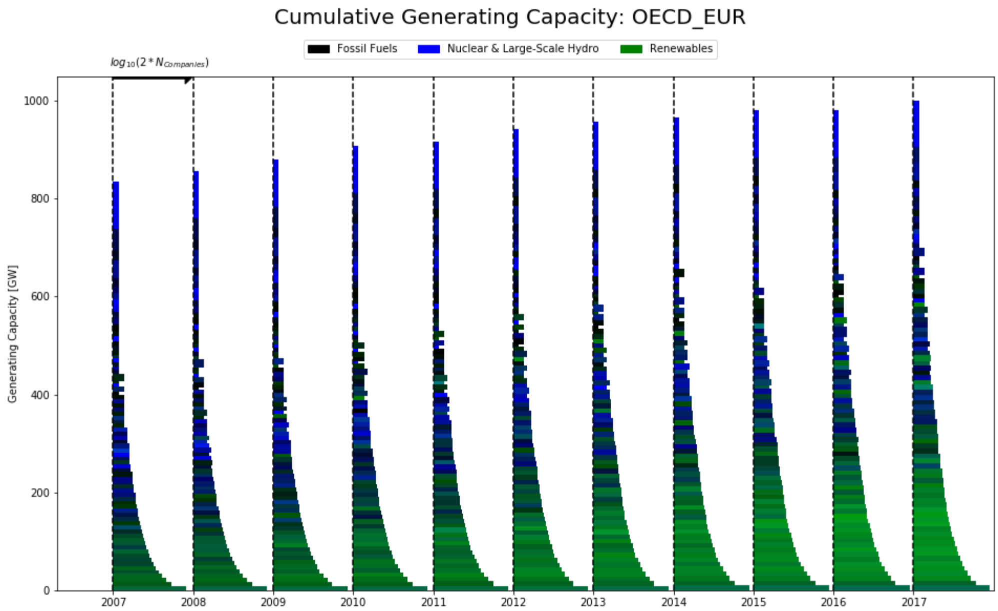

Figure A1h: Cumulative Generating Capacity, OECD_PAC

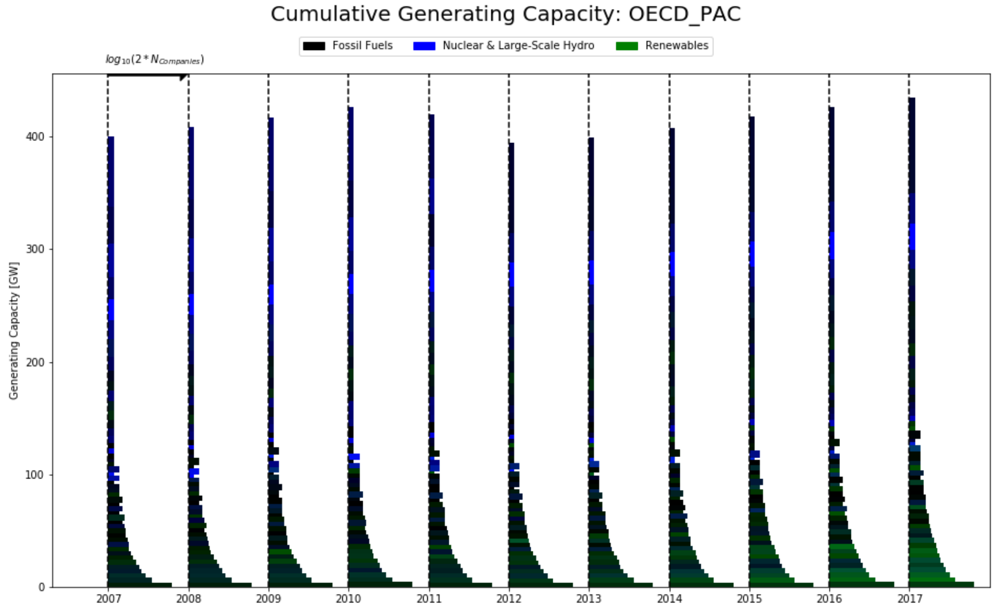

Figure A1i: Cumulative Generating Capacity, OTHERX

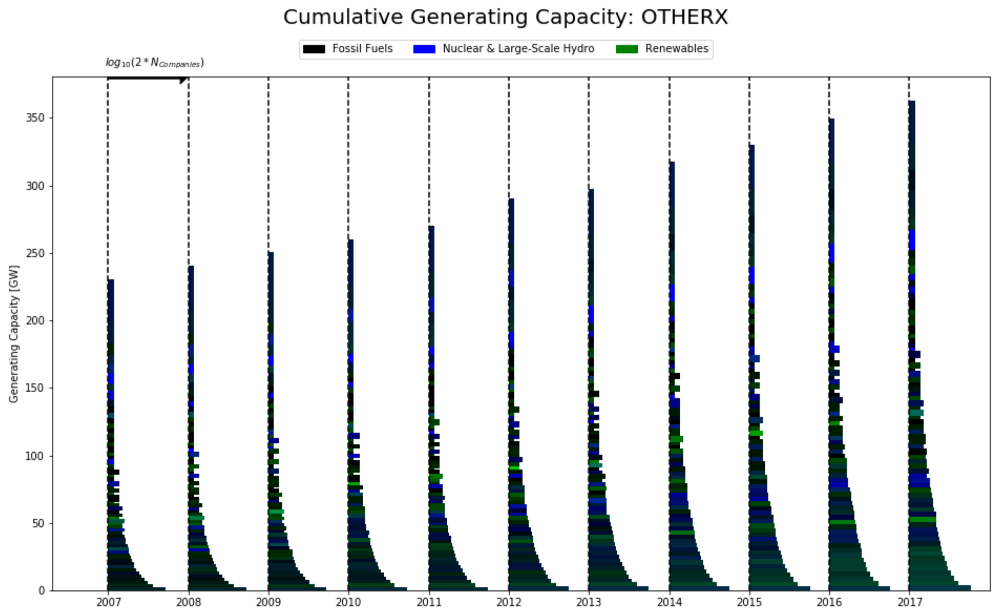

Figure A1j: Cumulative Generating Capacity, TE

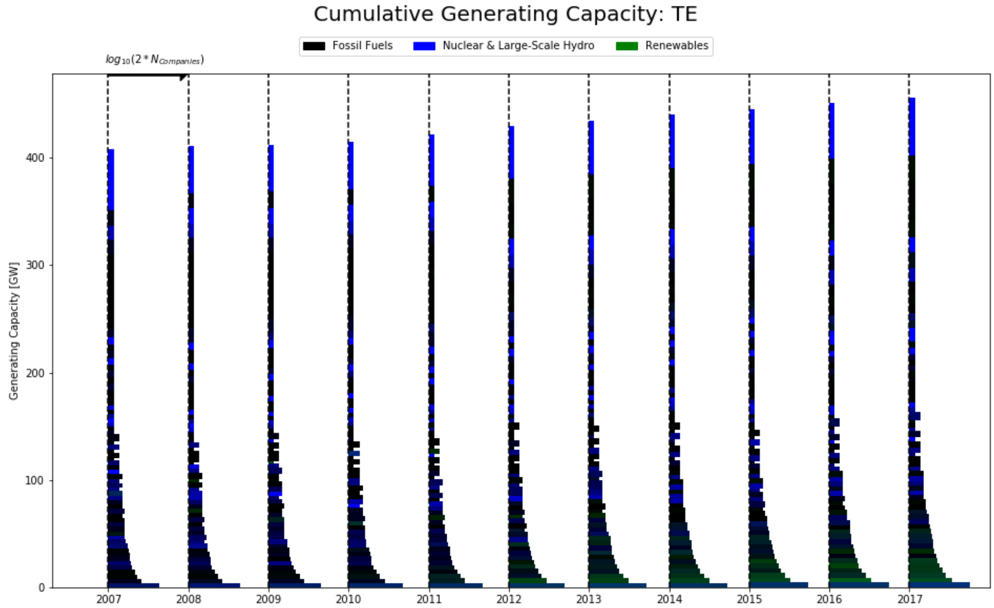

Figure A1h: Cumulative Generating Capacity, US