Simulating the effects of P2P grid proliferation on the EU non-renewable energy market

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***Abstract* -** The EU energy market is seeing a progressive transition towards the increasing usage of sustainable energy sources so as to meet the sustainable development goals of 2030. In this context a plethora of new systems are being considered for large scale implementation, one of which is Peer to Peer (P2P) energy networks. The latter allow individuals to consume and trade self-generated energy (from sources like solar panels) with other individuals that have attached themselves to the P2P grid. A growing body of research has sought to generate accurate ABM models to simulate the impact that P2P system implementation could have on the energy dynamics of local communities. Different models have concentrated their efforts on differing aspects of P2P proliferation, spanning from economic to environmental and social considerations. However, current research lacks the investigation of the potential impact that such systems could have on entire countries' energy dynamics and on a wider international scale. In this paper we thus aim to observe how the proliferation of a P2P system may affect the electricity trades from non-renewable energy sources between EU countries. To achieve this, we propose a new ABM model capable of modeling the evolution of an early-stage P2P system in a European country of choice. Results have shown a positive impact of the P2P spreading on the reduction of electricity dependencies from non-renewable energy sources across EU countries, and how the proposed ABM allows an accurate modelling of the differing proliferation patterns of P2P systems across the countries being modelled.

Keywords: Peer-to-peer networks, electrical energy, sustainability, Europe

1. Introduction

1.1: Context and Literature Review

Peer to peer energy trading is a relatively new technology. Distributed renewable methods for generating energy, like P2P systems, currently represent only 1% of global electricity generation, although they have increased considerably in the world in the last decade [1]. Indeed, the advantages they could bring are numerous, ranging from greater flexibility in energy management, to the absence of the need for costly intermediaries amongst trades and a transition to a greener energy production source [1]. For these reasons such technology is of great interest, especially for the European Union (EU), who is allocating considerable investments in the implementation and research of innovative ways to become more energy independent and have less of a polluting impact when it comes to the sources utilized to generate said energy [2]. In its simplest form a P2P network works by having two key classes of players interact to share energy in an environment termed as grid. One such class of players are the Prosumers, individuals who are able to generate their own energy through tools like solar panels. They can thus be self-sufficient, selling excess energy to others in the grid, but are not guaranteed to be so, thus also being customers of other prosumers in the grid themselves. A second class of players are the Consumers, individuals who are interested in buying such energy from Prosumers but do not have the ability to generate their own. Indeed, the latter are usually connected to the grid as they are either in proximity of Prosumers or want to benefit from the generally cheaper costs of energy from such a system compared to the normal grid [3].

Due to the transformative impacts that such technology could have, but also to its currently high implementation costs, a growing body of research has focused its efforts on utilizing computational modeling techniques to better assess the potential impact that the implementation of such systems could have. Indeed, as many countries currently also lack policies and laws to regulate P2P systems, simulating how the latter can work and the impact that they can have could also be important to inform governments on how to enact the most effective laws. A particularly popular methodology has been the usage of Agent Based Modelling (ABM). ABM is an approach that utilizes computational methods and behavioral dynamics to create models where agents, which are a representation of individuals or organizations, can interact with each other and with the environment [4]. Because such a method allows agents to have heterogeneous preferences that represent how decisions are taken in the real world, it is vastly favored to model complex systems such as P2P networks [5]. Indeed, classical models for P2P networks require the representation of complex interactions between two types of agents, namely the previously defined Prosumers and Consumers.

At present, modeling efforts have focused on evaluating the potential effect that P2P system implementation at a local level could have on varied spheres of life. Currently, the primary energy generation method considered for Prosumers in such models has been solar panels. This is due to its currently greater commercial availability compared to other available methods. As such the resilience of such systems under different weather conditions has been widely tested. Indeed, a limitation of solar panels is that they are expected to realistically produce no energy on rainy days and half of what they would produce on a sunny day when it is cloudy [5]. Existing models have however highlighted the resilience and effectiveness of such systems under the varying weather conditions communities are normally exposed to [6, 7]. Such results are both encouraging when it comes to the effectiveness of P2P systems, but also point at the saliency that weather considerations have when it comes to a representative modeling and assessment of such systems.

In addition, the importance of economic aspects for the effectiveness and development of P2P systems has also been researched. Studies such as those of [5] and [8] have developed P2P model where agents are able to trade under different business models and economic conditions in small communities. These have indeed highlighted the significant effect that the socio-economic conditions of agents have on the development and performance of P2P systems, thus emphasizing the importance of their consideration when building such models. Indeed, amongst the different socio-economic variables, income has been repeatedly shown to be a fundamental variable for correctly predicting agents' behavior [9] since also in reality individuals greatly evaluate the economic aspect of investments for their convenience [10].

Furthermore, it is also important to highlight how individuals are influenced by the social context in which they live, as their civic sense is conditioned by their desire to imitate their neighbors. This process has been described through a variable known as peer effect, having been shown to have a huge impact on energy decisions. Indeed, in the case of the P2P systems, research by [11] and [10], has highlighted how agents who are not part of such a system yet felt an increasing pressure to join it the more the number of their neighbors who belonged to the system increased. Specifically, the presence of Consumers seemed to have a bigger impact than that of Prosumers. Indeed, the peer effect is also strong when considering the decision to install solar panels in local communities as found by [12]. The same research also highlighted the strong influence that public subsidies can have on deciding whether to invest in such energy systems, especially if the former are certain to continue to be erogated in the future.

1.2: Contributions

Current literature presents valuable insights into the usage of ABM to implement accurate models of P2P networks, emphasizing the importance that a series of variables have in affecting the choices, behaviors and attitudes of individuals in such a system. Indeed, while these are all features of great importance for a representative implementation, current literature is limited to assessing such implementations on contained local communities, missing an in-depth analysis on how these P2P systems could be extended to evaluate their impact on larger energy systems, such as that of a country. This becomes especially salient when considering that literature does indeed hint at the fact that an individual's change in energy behavior, if scaled up, can have significant effects on the policies of a country [13]. Furthermore, while lacking an actual implementation a body of papers agrees that current models would need to be adapted to account for the effect that living in different countries could have on the agents, due to differing cultural, institutional, and climatic characteristics [11]. Development of such a model would then be important to start to evaluate the impact that P2P grids could have on large scale, evolving energy markets such as the European one. Considering the above limitations in the current literature, this paper seeks to address them by answering two research questions:

- Is it possible to implement a new ABM model capable of simulating the evolution, and thus the energy output, of an early-stage P2P system in a country of choice?
- Provided the implementation of the above model, what would be the potential effect that the proliferation of P2P systems could have on the network of trades of non-renewable energy for electricity generation amongst the top 10 EU economies?

The paper will thus attempt to extend insights gathered from micro level research on P2P modelling implementations to a macro-economic perspective of the relationships between countries for the exchange of non-renewables, offering a unique examination of the potential of P2P systems.

2. Materials and Methods

2.1: ABM tools and initial considerations

In order to construct and implement the model we utilized Python, specifically building on the Mesa package and its Model and Agent classes [14]. In addition, before a more detailed model breakdown it is important to mention a further theoretical consideration we made while designing our new model. Indeed, existing models currently do not consider a third class of agents; individuals who are not connected to the P2P system, which we termed 'Detached'. Given the fact that many countries seek to understand how such P2P systems could evolve and proliferate amongst their citizens once initial adoption by some has taken place, and that this is also a key aim of our paper, it was thus important to understand the pattern with which new people would join the shared grid once it was started. Indeed, the potential increase of Consumers as new people join the shared grid can have important effects on the evolution dynamics of the P2P System both in terms of costs and of energy production [5]. Given their importance, and the current absence in the literature, we thus decided to explicitly include a new class of agents in our P2P model.

2.2: Schelling Model - Agents and Topography

As mentioned, a big factor affecting technology adoption is an individual's economic status [9]. This would imply that for the proposed model different areas of a country would have to evolve at different paces depending on their wealth. Thus, our first task was to be able to simulate the different economic identities present within each country. As social behavior tends to organize settlements by forming neighborhoods largely segmented according to the level of income of the residents [15], we designed a customized Schelling Model to mimic such behavior. This model classified agents as happy or not according to whether the fraction of their neighbors (we utilized an 8-neighbor Moore neighborhood) that belonged to their same income class, exceeded a certain threshold. For each agent, we thus assigned an income class (high, middle or low) through a random draw from the country's wealth distribution taken from [16]. We then placed agents on a 2D squared grid, whose dimensions were proportional to each country's population, gathered from [17]. For computational concerns we rescaled populations by a factor of 10,000 if the country population exceeded 10M, and by 1,000 otherwise. At each step, agents were then free to move according to their current condition, namely: they would stay still when they were happy and move towards a random empty place otherwise. As a happiness threshold for this model we utilized each country's Gini Index (taken from [18]). This is a measure of wealth inequality where, the higher the index, the higher the income inequality in the country, thus implying that having similar neighbors in terms of income will be harder, leading to a higher happiness threshold and greater segregation. In turn, this allowed us to uniquely model a system of heterogeneous regions representing the economic segregation across social classes for each country. Moreover, the model accounted for the countries' differences in terms of densities. Such a parameter was indeed core in a Schelling Model, as the greater presence of empty spaces would allow an easier movement of the agents. The density for all the models was thus made of two components, a default value (0.5), common to all and needed to ensure that we did not have an excessive amount of empty spaces, and a country specific add on. The latter was calculated as the fraction of each country's density (gathered from [17]) with respect to the most dense European Country (Malta), which was later excluded from the analysis having a density of 1 under the system described. This exclusion was judged as not significant since we were focusing on modelling the top ten EU economies of which this country is not part of.

For each country, we then ran the model until it reached convergence, (i.e. all agents were satisfied with their place in the system). By, for example, observing Figure 1, which reports the resulting grid from a Schelling simulation in Italy, it is possible to notice how the population is indeed stratified into several neighborhoods according to the three income levels. This subdivision then allowed subsequent steps in the model to effectively replicate the P2P proliferation, where wealthier areas evolved faster, having a knock on effect on areas directly around them, while poorer areas took more time.

2.3: P2P Model - Agents and Topography

Following the income configuration of agents in space according to the Schelling model, we proceeded with a second stratification needed to implement the P2P Model. We maintained the same 2D squared grid with Moore Neighborhood and further stratified agents according to their role within a P2P system. This was either that of 'Prosumer', 'Consumer' or 'Detached', being allocated through a random draw from a fabricated distribution. The latter was the same for all the countries modelled being built to represent a country at a very early stage of adoption. Indeed, as one of the aims of our paper was to simulate the potential impact that such system could have, and considering that many EU countries still have not employed the usage of P2P system, we could not rely on existing Prosumer, Consumer and Detached distributions. We thus assumed a starting situation featuring 5% of prosumers, 10% of consumers and 85% of detached, namely a minimum value that was enough for the spreading process to successfully start in the system during the simulated time window. It is important to note that since we were interested in modelling the spread of the P2P system only the agent's role in the grid would be able to evolve, changing from detached to consumer and from consumer to prosumer, while the economic state was static over time.

2.4: Agent Objectives and Behaviors

The core element affecting the model evolution was the capability of each agent to invest in solar panels. At the beginning of each iteration, agents were assigned a fictitious monetary measure associated to their electricity consumptions in the following way: first, we retrieved from [19] the average electricity consumption per country, subsequently, we calculated the weights for the income classes as the percentage variation in European average income (taken from [20]) among the three wealth classes (high, middle and low income), finally obtaining the weighted amount of electricity usage. To have such amounts in economics terms, we then assigned to the agents the aforementioned quantity multiplied by the average price paid of electricity in the specific modelled country taken from [21]. At each model iteration, the agents then recorded a monetary saving (coins) proportional to the amount of electricity they were able to purchase directly from the cheaper P2P system. Agents were programmed to exhibit a goal directed behavior whereby they would try to maximize the amount of coins saved. It is important to note that the cost of energy of the P2P grid is lower than the one of the normal grid as per indications made by [3, 6]. We calculated the cost of the electricity in the P2P grid as a function of the number of Prosumers present in the system, as this price will drop as more Prosumers become part of the grid [5]. In addition, based on the role in the grid each agent exhibited different behaviors:

Detached: At each step the Detached would first have their allocated coins for that day brought to 0, since they would have bought all their electricity from the grid, thus having a cost equal to the amount of coins allocated for their energy needs. They would then try to transition to the 'Consumer' class through the 'peer effect' mentioned previously. The latter consisted in the agent checking their neighborhood to see if the amount of people around them who were consumers or prosumers would exceed a specific threshold. If this were the case, according to a specific probability, they would then turn their role into 'Consumer', joining the P2P grid. While the weights associated to the influence that a prosumer and a consumer would have in an agent's transitioning decision (and thus whether it passed the threshold) were taken from relevant regression studies in [22], the actual threshold value and probability value itself were manually tuned through a BatchRunner routine. Indeed, as to our knowledge this is the first empirical model to include the transition from Detached to Consumer in a P2P system, implying that there was a lack of data and additional studies pointing at exact values for these variables. We thus selected ranges for the two that generated a gradual and sensible decrease in the population of 'Detached' individuals (as seen in Figure 2) and overall realistic outputs for the model (see Results and Discussion section). We then ran the model using this value range (see Italy_ABM.ipynb) and took as final output the average over all the Batch Runner's runs.

Consumer: If the consumer had no prosumers in their neighborhood, they would default to buying all electricity from the grid, thus not saving any money. If instead prosumers were available in the neighborhood the Consumer would have its coins updated with savings equivalent to those that they would make by buying energy from said Prosumers (the trade logic described in the Prosumer section). Following the energy trade, the agent would then check whether they had enough coins to buy solar panels. This was done by seeing if their coins exceeded a 'cost threshold'. The latter was calculated by multiplying the amount of solar panels desired (this changed depending on the social class, which would have different purchasing abilities, as per quantities gathered from [23]) with the watt power level of the commercial panels installed (taken from [24]) and the price of the electricity in the P2P grid (as a proxy for the cost of installing the equivalent of 1 watt of solar panels). Indeed, this is the process through which installation costs of solar panels are calculated in the market, adjusted through the aforementioned proxy to be able to work in light of our P2P system. Indeed, the price of electricity in the P2P grid will drop as more people produce electricity [5], likewise as a technology spreads its implementation cost usually becomes cheaper, thus justifying the use of this proxy. If the threshold was exceeded, then the agent decided to invest based on a probabilistic decision rule. In fact, they invested with a probability that depended on the measure of subsidies and environmentalism present in the country being modeled as found in [25, 26]. We rescaled this data to be able to be consistent with our model. The score for subsidy came from a ranking system based on data in [26] where countries where ranked higher if they had a higher total score amongst the various subsidy dimensions present in the dataset. Based on their ranking position they were then assigned a higher or lower subsidy score on a decimal scale. As for environmentalism it was also an average score of the points assigned to the 'environmental section' that composed the original data. The final probability is calculated through a logit link built on regression coefficients found in [22] for these two dimensions. If the probabilistic decision rule is positive the agent will change its status into 'Prosumer' and will start generating electricity at the next iteration.

Prosumer: At each step the Prosumer generated solar energy as a function of the weather in that iteration (day), the sun hours available, the amount of solar panels installed, and their respective power. Weather conditions and sun hours were drawn from the actual distributions present for the country modelled, retrieved respectively from [27] and [28]. As explained in the Consumer section the quantity of solar panels installed depended on the economic class of the agent. The Prosumer would then check whether the amount of energy they had produced was greater or lower than their energy requirements.

If the energy produced was lower than that required, they would buy the remainder from the normal grid and update their coins with the savings made by self-fulfilling a part of their energy requirements. Indeed, in order to try and increase their energy generation and thus their savings, Prosumers would then check whether their coins exceeded a 'cost threshold' representing the price difference for panels with a greater power compared to the ones they had installed. The values for the different panel powers where taken to be the quartiles of the distribution of commercial panel powers taken from [24]. We utilized quartiles so as to not have an excessive amount of upgrading steps but still enough granularity to replicate such an investing process. The threshold itself was calculated following the same logic discussed in the Consumer section. If the threshold was indeed exceeded the same probabilistic rule described for Consumers would then decide whether to invest and upgrade the output of their panels. Indeed, the same rule was applied as also Prosumers would be affected by the subsidy and environmentalism values present in the country, as suggested by [22].

If a Prosumer instead produced more energy than they required, their coins would be updated accordingly accounting for the absence of a need to buy energy from the outside grid.

They would then proceed to distribute the energy to the neighbors who need it. The distribution process was done by filtering only neighbors of the said Prosumer that were 'Consumers' or 'Prosumers' (thus attached to the P2P grid). The excess energy was then distributed in equal parts to the aforementioned eligible neighbors that still required energy. If the specific neighbor required less energy than what was given to them, the amount would be adjusted to match their actual energy needs. Through this step, each of the agents who received energy would also have their savings updated according to how much energy they were distributed by the Prosumers in the P2P grid. Once the distribution was over, the Prosumer would then check if they exceeded the 'cost threshold' and potentially invest in more powerful panels as described earlier.

It is important to note that at each iteration agents are activated with a specific order according to their role. Indeed, the Prosumers only started with a partial move first, calculating the energy they produced on that day. This allowed the model to differentiate those prosumers producing more than what they needed from those producing less. The latter could thus be 'flagged' as needing energy from other Prosumers in the distribution process described previously. Detached then moved second as they were not interested in the energy production process of the Prosumers. These were then followed by the Consumers who would thus be allowed to calculate their needs and also be flagged as needing more energy from other Prosumers. Finally, those Prosumers who do indeed produce more than they require would complete the iteration by distributing energy to the flagged agents. While such an order essentially does not allow Consumers to potentially invest in the first step it essentially acts as a burn-in step, ensuring a smooth and correct run of the model in subsequent iterations (the full model logic is available as a flow chart in appendix).

2.5: Network Construction

To map the relationships between the different countries in the EU in terms of non-renewables trades, we constructed a weighted directed network. Such a network enables to assess both the strength of the relationship, through the presence of weighted edges, and the direction of the links, permitting the identification of exporters and importers. The construction of the network involves three steps: determining the amount and the sources of non-renewables imported, identifying the portion of non-renewables imported used for electricity generation and, finally, determining the appropriate weights to give to the network.

Data for the first step was obtained from Eurostat [29] which provides, for all EU countries, the quantity of natural gas, coal and oil imported in 2020 as well as the sources of the imports. Subsequently, through data available from the International Energy Agency (IEA), we determined the quantity of electricity generated in 2020 from each source by each country [30]. Next, we calculated the ratio between the electricity generated from each of the non-renewable sources and the total consumption of electricity in 2020 obtained from the IEA [30]. We assumed that the quantity of each non-renewable imported destined for electricity generation was equal to the ratios just computed. Finally, we were able to trace the dependencies of non-renewables for energy production for each EU country, enabling the construction of the network reported in Figure 3. To determine the positioning of the different nodes we used the Fruchterman-Reingold force-directed algorithm, which performs well on large networks and determines the positioning of the nodes based on their connectedness with the other nodes [31]. Thus, the more highly connected nodes will be positioned around the center of the network.

In Figure 3, three different types of nodes can be observed. Yellow nodes refer to countries that are outside the EU and that export non-renewables to EU members, their size is fixed. Green nodes instead refer to EU countries that were excluded from the subsequent ABM analysis, their size is set equal to that of non-EU countries. Finally, blue nodes refer to the top ten EU economies that are studied in the following sections. The size of those nodes is determined by the ratio of the electricity generated from imports of non-renewables and the total consumption of electricity by the country. Therefore, the larger the node, the more it is dependent on other countries to satisfy its internal demand for electricity. It is also worth noting that there are countries for which the electricity generated by the imports is higher than that consumed in a year. The two reasons behind this fact are the following: countries could be trading energy and countries could acquire extra non-renewables and store them for usage in later periods. Lastly, as previously mentioned, the edge size is not constant but rather has a specific weight which refers to the ratio of electricity generated from non-renewable imports from the specific country with the total amount of electricity generated from non-renewable imports. Thus, the thicker the edge, the greater the dependency to that particular country.

3. Calculations and Results

3.1: Simulation Procedure

For each of the top 10 EU economies, we ran a P2P model utilizing the country specific variables mentioned in section 2.2.4. Each simulation was run for 365 iterations, representing a year, with varying values for: the peer effect threshold, the probability values of the Detached class mentioned in section 2.2.4, and Schelling matrices. The latter was included so that, by averaging the total electricity produced across different runs, more robust results, that took into account the stochastic nature of the Schelling model, were obtained. The simulations were carried out via a Batch Runner and the final electricity output was rescaled by the population scaling parameter explained in section 2.2.2 so as to have an energy output that now took into account the entire population of the modeled country.

3.2: Network Dynamics

Following the ABM simulation, we collected the amount of electricity that was produced in the simulated time window in each country, and we redistributed such reduction to in-degree countries in the following way. First, we reduced the links that each country had with non-EU members in a proportional manner with the current dependency to the specific country. We iteratively distributed the reduction in energy until there were either no more reductions to allocate or the links to non-EU members became zero. In the latter case, we then distributed the remaining reductions in a proportional manner to EU countries, where the current dependencies acted as a weight. Second, we shrunk the nodes of the simulated countries by considering the new quantity of non-renewables for energy production that had to be imported.

The reason for the aforementioned repartition of energy reductions stems from the consideration that EU members are more likely to have stronger relations with one another compared to with non-EU members. The updated network is reported in Figure 4.The analysis of the simulation results on the network are divided into a focus on: the network of only the considered EU countries, the EU network and, the network with non-EU members.

Considering the effects of P2P on the links between the top ten EU economies, it is possible to notice a reduction in the total number of edges (-22.5%), a reduction in the average degree (from 4 to 3.1) and an increase in the strength of the relationships of the considered countries (+26.7%). The reasons behind the first two effects are due to France and Sweden. Those two economies, in fact, imported a small quantity of non-renewables prior to the P2P simulation thanks to, respectively, the presence of multiple nuclear power reactors [32] and the vast usage of nuclear, hydroelectric and wind power [30]. The increase in the strength of the edges is caused by the redistribution of energy decreases to non-EU members and to the elimination of weak in-degrees for France and Sweden. The results on the network are reported in figure 5 in the appendix.

Similar results are observed when the entire EU network is considered, as reported in figure 6 of the appendix. In fact, there is a decrease in the number of edges of -25% and, a decrease in the average degree from 2.89 to 2.16. Additionally, there is an increase of 33.3% of the average edge weight. It is worth pointing out that the average edge weight compared to the network of only the top ten EU economies is lower, indicating the presence of weak energy trade between the considered countries and the rest of the EU. The main reasons for the observed changes are similar to the aforementioned ones, namely: the newly achieved independence of France and Sweden and the link reduction mechanism. Moreover, the lower average degree stems from the fact that only exporting relationships are considered for the added EU members.

More significant effects of P2P are observed in the network of non-EU members. In this case, in fact, there is a decrease of the number of edges (-17%), a decrease in the average edge weight (-23%) and, a drop in the average degree (from 4.49 to 3.72). Overall, through the repartition of energy decreases, it is possible to notice a greater degree of diversification for the considered EU countries as they now depend less on a single energy provider compared to before. Moreover, the positioning of two key exporting countries, Russia and Norway, has changed following the P2P simulation, indicating a decrease in their importance as exporters compared to before. Figure 7 in the appendix reports the network before and after the simulation.

Additionally, the node sizes of all the considered countries report some shrinkage, contrary to the results observed in the previous networks. As can be seen in Table 1, there are heterogeneities of the effects of the P2P system. In fact, the standard deviation of the reported changes in node size is 37.5 percentage points. Such changes are indeed consistent with the current profiles of each of these countries. Indeed, we could group these 10 economies into three major types of reductions. We have large reducers like France, Sweden and Poland who are able to cut a substantial amount of energy imports, with a reduction of their nodes size, representing their energy dependency, of more than 70%. Indeed, these are all countries that rely heavily on self-production, either through Nuclear (France), Hydroelectric (Sweden) or Coal (Poland). The latter would thus not only need to import less, but also be more inclined towards pushing further technologies for self-generation of energy as it is already part of their energy strategy. We then have a second band made of countries that have a medium reduction in their dependencies going from 20% up to 56 %. These are all countries that are characterized by strong and resilient economies which however still present a consistent reliance on outside energy sources. Indeed, our model is consistent in outputting a more conservative decrease for such countries since the latter have been slower and more reticent in adopting technologies to further increase their energy independence and to evolve from more traditional energy sources. A great example from a country in that group comes from Germany, who has maintained a strong dependency on gas while being strongly opposed from implementing technology such as autonomous nuclear energy production [33]. Finally, a third group of countries presents smaller reductions below 10%. These all tend to be smallest of these top economies, where the population is likely to be less willing to start to adopt the technology widely in the earlier stages of its lifecycle, something the model is able to capture in its results. In conclusion, while there is no existing data yet on the potential energy generation of P2P systems in these countries that could act as validation for our model, the fact that the model is able to represent energy investment patterns for countries amongst this group does provide an initially satisfactory theoretical validation to its results.

Table 1: Node sizes of the top ten economies following the P2P simulation
The table below shows the node sizes of the top ten EU economies before and after the P2P simulation. Each node size is the ratio between the amount of electricity generated from imports of non-renewables and the total energy consumption in the country.

Country	**Node Sizes Before**	**Node Sizes After**	**Change**
Austria	0.316386	0.226421	-28.44%
Belgium	0.862875	0.783416	-9.21%
France	0.058058	0.000000	-100.00%
Germany	0.324989	0.208719	-35.78%
Ireland	2.074293	1.989726	-4.08%
Italy	1.120833	0.890319	-20.57%
Netherland	2.986237	2.883457	-3.44%
Poland	0.181730	0.046373	-74.48%
Spain	0.437530	0.188319	-56.96%
Sweden	0.000693	0.000000	-100.00%

3.3: Variable impact

Overall, following the P2P simulation, the main results observed are a decrease in the number of edges, a decrease in the strength of the ties, a decrease in the average degree of the nodes, and, finally, a decrease in the average node size. As previously mentioned, there is heterogeneity in the reductions of node sizes in the different countries. Given the vast number of features considered per country, we, thus, decided to run an OLS regression to better investigate the relationships between the features and the amount of electricity produced. In such regression, we decided to transform the amount of electricity produced in logs for two different reasons. First, through a log transformation, the coefficients of the regression become more interpretable as they are now expressing the percentage change in the electricity produced following changes to the regressors. Second, the distribution of the electricity produced is skewed and, through a log transformation, it becomes closer to a normal one, enabling the regression to better fit. The results of such regression are reported in table 2 of the appendix. It is possible to note that all the different coefficients are statistically significant and the reported R^2 is extremely high. We checked for the presence of collinearity via the variance inflation factor and reported that collinearity was not a concern. In fact, the average VIF score was of 2.86 and the highest VIF was 6.28, well below the value of 10, commonly used as threshold [34]. These results were expected as we constructed the data generating process through the ABM model. Still, investigating the relationships between the different variables and the electricity produced can give important insights. Overall, the different regressors can be grouped into four main categories: weather, demography, model specific and social variables.

Weather variables include: the probability of rainy days, cloudy ones and the number of sun hours in the country. The probability of sunny days had to be excluded because it is collinear with the probability of rainy and cloudy days. It is possible to notice the negative impact associated with bad weather and electricity production. Overall, per each percentage point increase in the probability of rain, there is an associated decrease of 993% in electricity production. Similar results are observed for cloudy days, but in this case, the impact is of lower size thanks to the fact that solar panels, under our model, can produce electricity with lower efficiency during these days.

Finally, sun hours have the expected relationship with the electricity produced as an additional sun hour is related to an increase of 24% of electricity production. It is worth noting how the magnitude changes between the weather variables, suggesting that rainy days have a greater impact compared to the sun-hours and cloudy days.

Demographic variables, instead, refer to the country's population and density. To make the former coefficient more interpretable, we decided to express it in millions. The results of the OLS regression point to a negative relationship between density and the electricity produced and a positive one between population and electricity produced. By further exploring the first result, we were able to observe that density has a strong correlation with bad weather variables, namely: fewer sun-hours and a higher chance of rainy days, thus explaining part of its negative coefficient. The stand-alone negative correlation between density and electricity produced can also be explained by the fact that, through lower density, the neighborhood around a prosumer may not be fully populated, entailing that electricity is going to be shared with fewer agents, ultimately increasing the diffusion of P2P. On the other hand, the positive relationship between population and electricity produced likely relates to the fact that in more populated countries, the overall total number of solar panels that can be installed is greater than that of smaller ones. Moreover, the correlations reported in table 3, indicate that more populated states are associated with better overall weather.

Model-specific variables encompass the detached threshold and the probability of becoming a consumer. In this regard, the presence of a very significant, magnitude-wise, coefficient for the latter variable justifies the usage of a varied set of values when constructing and tuning the model, so as to generate results that are more robust in the absence of new empirical studies on the matter. Finally, and most importantly, social variables include subsidies and environmentalism. A measure of subsidies, as mentioned before, indicates the overall government aid provided when acquiring solar panels. As expected, there is a positive relationship with the quantity of electricity produced indicating that greater government aid leads to a greater adoption of solar panels.

Environmentalism, instead, tries to measure the impact of green thinking within a country. Surprisingly, such variable is negatively related with the electricity produced. This result was further explored with an OLS regression in which environmentalism was set as a dependent variable and multiple other regressors were included. The results of this regression are reported in table 4. Among the various coefficients, subsidies have a negative and strong relationship with environmentalism, suggesting that countries that provide more subsidies are those in which the inhabitants care less for the environment. In greener countries instead, a lower quantity of subsidies is motivated by a lack of need as green goals can be accomplished through the high levels of environmentalism present.

Moreover, it appears that denser countries tend to be less green. Such a result ties back with the aforementioned negative relationship between density and green energy, thus explaining part of the negative relationship present between environmentalism and the quantity of solar energy produced. Finally, there is a strong and highly significant positive relationship between environmentalism and the average price for electricity in the country. The latter variable has a negative and strong relationship with the total electricity produced in a country, thus influencing the negative coefficient observed for environmentalism. Due to multicollinearity problems, such variable could not be included in the first OLS regression that was run.

3.4: Class transition Dynamics

The results of the ABM enabled us to also understand the evolution of the detached, consumers, and prosumers across the simulated year. Such trends, obtained by averaging and constructing a confidence band around the results coming from the different combinations of parameters of the batch runner, were common to all the simulated countries. For illustrative purposes, the results from Italy are reported in figure 7. Overall, the transitions among the different groups closely mirror those of a SIR compartmental model. In fact, similarities in the dynamics can be observed between: detached and susceptibles, consumers and infected, and between prosumers and recovered. As it can be seen, there is a linear decrease in the number of detached. This result is in line with expectations as, the movement from detached to consumer is affected only by the number of consumers and prosumers that are neighbors. Magnitude-wise, the number of detached at the end of the simulation is still elevated, in line with our expectations. In fact, a too high decrease in such category would be highly unrealistic as individuals are very likely to take time before switching, even partially, between energy providers.

The consumers, on the other hand, showcase a more distinct pattern. In fact, in the first fifty days of the simulation, there is a sharp decline in their numbers. The reasoning behind this is that, during such period, the consumers that were neighbors of prosumers were able to save enough coins to proceed with the investment in solar panels, thus becoming prosumers. Following the first fifty days, linear growth is present. Such result is motivated by the fact that the transitions of individuals from detached to consumers exceed those from consumers to prosumers. In fact, such transition will take place only if the savings obtained by purchasing electricity from a prosumer neighbor exceed a pre-specified threshold. Given the limited number of prosumers, making such movement will be more difficult compared to moving from detached to consumer. In the latter case, the only parameter affecting the transition will be given by the neighboring consumers and prosumers. Thanks to higher numbers of this set of individuals moving from detached to consumer will have a greater probability compared to moving from consumer to prosumer.

Finally, the prosumer dynamics showcase sharp growth in the first fifty days, the opposite of the trend for the consumers. The rationale behind such transition stems from the conversion to prosumers of consumers surrounded by neighboring prosumers, who were thus able to meet the requirements for the transition. Importantly, the small confidence band around such a trend suggests that across the different simulated models this is a consistent result. Additionally, following the fiftieth simulated day, small linear growth of both the number of prosumers and the confidence interval is observable. Such result is explained, as mentioned before, by the transition to prosumers dynamic. Instead, the growth in the confidence interval coincides with the effects of changes to the parameters governing the movement from detached to consumers. In particular, by varying such values, the number of detached that were able to transition each day to consumers varied considerably, thus affecting the evolution of consumers and, subsequently, the growth of prosumers.

4. Discussion

This paper sought to determine the impact that country specific P2P systems could have on the international dependencies of non-renewables used for electricity generation. To accomplish this goal, we constructed the network of non-renewable dependencies and, additionally, we designed country specific ABM models using multiple sources of real data. Following the simulations, multiple interesting results were gathered that can be grouped into: AMB dynamics effects and network related ones.

The first effects point to a common dynamic across countries for the three groups of agents in the model. In particular, for the detached, linear decrease over the simulated time window is observed. More interesting relations are instead observed for the consumers and prosumers. In fact, the first group exhibits a sharp decline in the first fifty days of the simulation and linear growth afterwards. This result is explained by the savings obtained by being surrounded by neighboring prosumers. In fact, through the level of segregation obtained by the Schelling model, it becomes very likely to have consumers amid prosumers, thus leading to this decline. The trend after the first fifty days converges to linear growth. The prosumers showcase a similar trend with sharp increase in the beginning of the simulation and linear growth in later stages. Additionally, this starting phenomenon is also robust to different model specifications as the confidence interval around it is fairly small.

The main effect on the network following the introduction of a P2P system is a decrease in the quantity of non-renewables that must be imported to satisfy internal demand. Further, we identified a greater spread of dependencies following the P2P simulation, as now countries depend less on imports from few key players. Finally, two countries, namely France and Sweden, were able to eliminate their in-degrees completely, thus becoming energy independent. Overall, large heterogeneities in such effects were detected and we were able to identify the main drivers behind them. Through an OLS regression, we determined four types of significant groups of variables, specifically: weather, demographic, model specific and social ones. The main relationships detected were as expected. In fact, we determined that weather variables had positive and significant, also magnitude wise, effects on the quantity of electricity produced in the simulated year. Demographic variables on the other hand pointed to a positive relationship between population size and electricity generation and at a negative one between density and the dependent variable. The latter was motivated by the fact that through lower density, the savings obtained from having prosumers as neighbors were distributed to fewer agents, making it easier to reach the saving threshold and transition to prosumers.

Model specific variables pointed at the significant impacts, both statistically and magnitude wise, of the two variables governing the transitions from detached to consumers, namely: the threshold to transition to consumers and the probability of transitioning once the threshold is met. Given their significance and provided that no real data could be practically gathered, we decided to include multiple values for these two parameters to make the results more robust. Finally, when studying social variables, we observed a positive effect of subsidies and a negative impact of environmentalism. Multiple explanations for the latter effect can be identified. Firstly, we identified a strong and negative relationship between subsidies and environmentalism, suggesting that countries in which individuals' environmentalism awareness is spread need much less subsidies to achieve green goals. Additionally, a positive relationship between density and environmentalism was observed which could explain part of the negative relationship with the electricity produced. Ultimately, the negative sign observed could also arise from the way in which the environmentalism index was constructed, bringing us to the limitations of this study.

Multiple limitations are related with this study. Firstly, to approximate the distribution of the agents on the grid, we had to use the Schelling model, which may be too simplistic and may not accurately represent the true locations of agents. Although we tried to account for some of the randomness of this procedure by using multiple Schelling matrices in our BatchRunner, acquiring more accurate mappings will be beneficial for future versions of this model. Secondly, due to the absence of quantitative data relating to subsidies, we had to transform qualitative measures, obtained from [28], into a quantitative one. Obtaining country level quantitative data could ameliorate the model. Thirdly, in the ABM construction some simplifying assumptions had to be introduced. In particular, we assumed that prosumers distributed electricity to their neighbors not via a trading dynamic, which would yield monetary benefits to the prosumers, but rather in an even manner. This entailed that some of the energy produced by the prosumers would be lost. More precisely, if the prosumer or consumer requires less energy that the prosumer is distributing the excess energy will be lost by the system. This limitation however does account for the fact that, typically, in energy trades there are inefficiencies leading to energy losses. Further, we assumed that at each time step, the extra electricity generated by prosumers will be redistributed, thus not contemplating the possibility of storing energy for later consumption. This was due to a further lack of data related on urban energy storage methods, also relatively new in the market. So as to not include further uncertainty and arbitrariness in the model the latter were thus excluded.

Given the promising results of the spread of P2P systems and, provided the current global situation relating to energy trade, further expansions of the ABM model here proposed should be introduced. More precisely, future research could further improve the quality of some of the data used as input to the model and it could expand on the sensitivity of the electricity generated to different government policies (i.e., changing the current energy subsidies). Furthermore, new research avenues could ameliorate the ABM model in different ways. First, more advanced models could explicitly model the energy trade among consumers and prosumers, thus enabling prosumers to obtain monetary gains through the sale of energy. Second, a global system of energy prices could be introduced to monitor the effect overtime of the proliferation of the P2P system on global trade. Third, more countries could be simulated to obtain a further differentiation of P2P effects. Fourth, for countries that are able to eliminate all energy imports, it could be insightful to explore how the newly generated solar energy could replace non-renewables in satisfying both internal and external electricity demand. Another greater layer of depth that could be added refers to the distribution of house types (i.e., condominiums, detached houses, …) in each country.

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Appendix

Figure 1: Italy Schelling Model

The figure reports the output of the Schelling Model run on Italy's features. The dimension of the grid represents a rescaled approximation of the Italian Population. The cells composing the grid are colored according to the level of income class the agent, present in the cell belongs to. In particular, yellow areas are the high income neighborhoods, green areas are the middle income neighborhoods, light blue areas are the low income ones and, finally, the dark blue cells are empty.

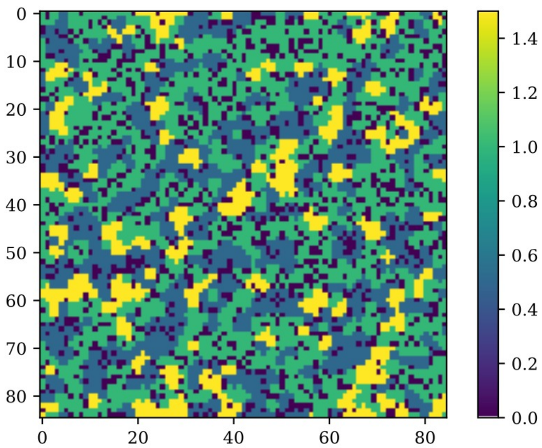


Figure 2: Evolution of Detached, Prosumers and Consumers during a one year time range through Italy BatchRunner iterations.

The figure reports the evolution of Detached, Prosumers and Consumer among Italy's iterations while controlling for different values of Detached Threshold, Detached probability to become Consumer and for several runs of the Schelling Model. The y-ax represents the number of agents, the x-ax represents the steps of the iterations. Finally, the marked line is the mean value,while the shades are the confidence bands, accounting for the variability across the iterations.

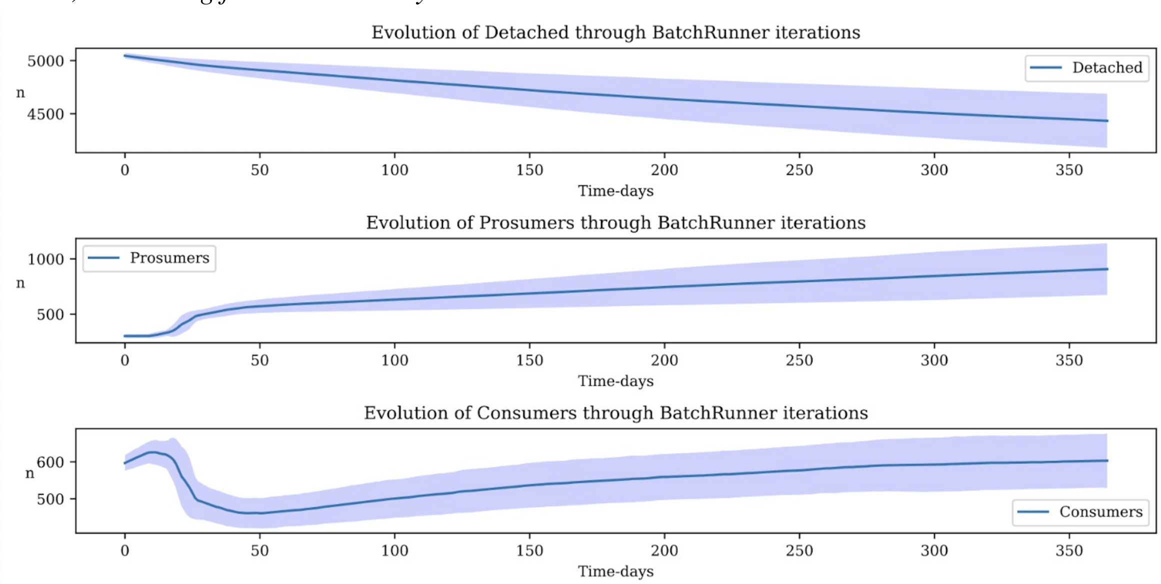


Figure 3: Current Network of Non-Renewables Trades

The figure reports the current network of non-renewables trades in the E.U. In particular, yellow nodes refer to Non-EU countries, green ones to EU-countries not analyzed through the ABM and the blue nodes refer to EU countries. The node size of EU members is determined by the ratio between the quantity of electricity generated from imports and the total amount of electricity consumed. Finally, the edge sizes are proportional to the dependency to the specific country.

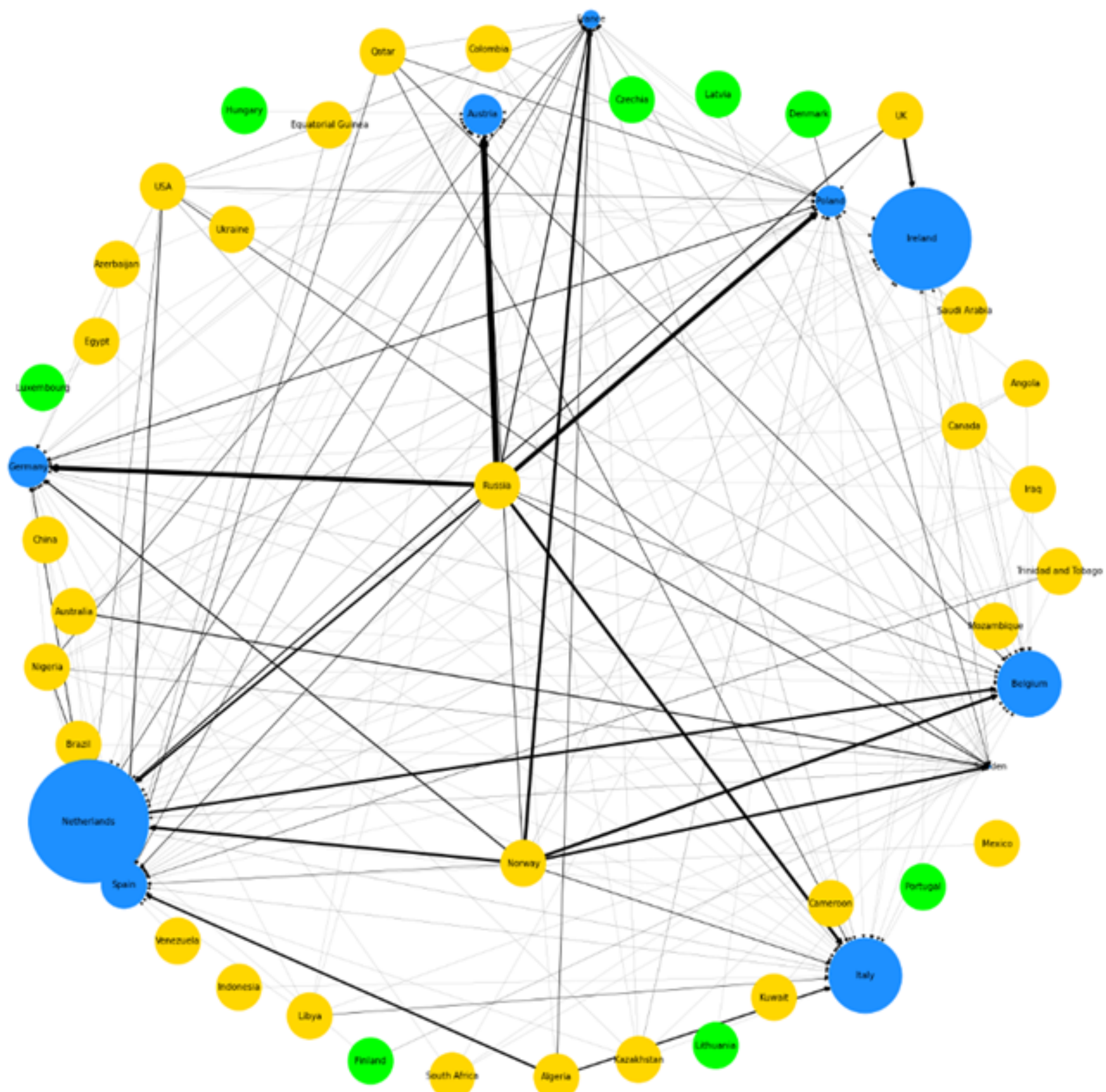


Figure 4: Updated Network Following the Simulation

The figure reports the updated network of non-renewables trades in the E.U. Important differences observable with the original network are the reduction in edge weight due to lower demand of non-renewables for energy production and the decrease in node sizes of the top 10 EU economies, due to higher self-sufficiency.

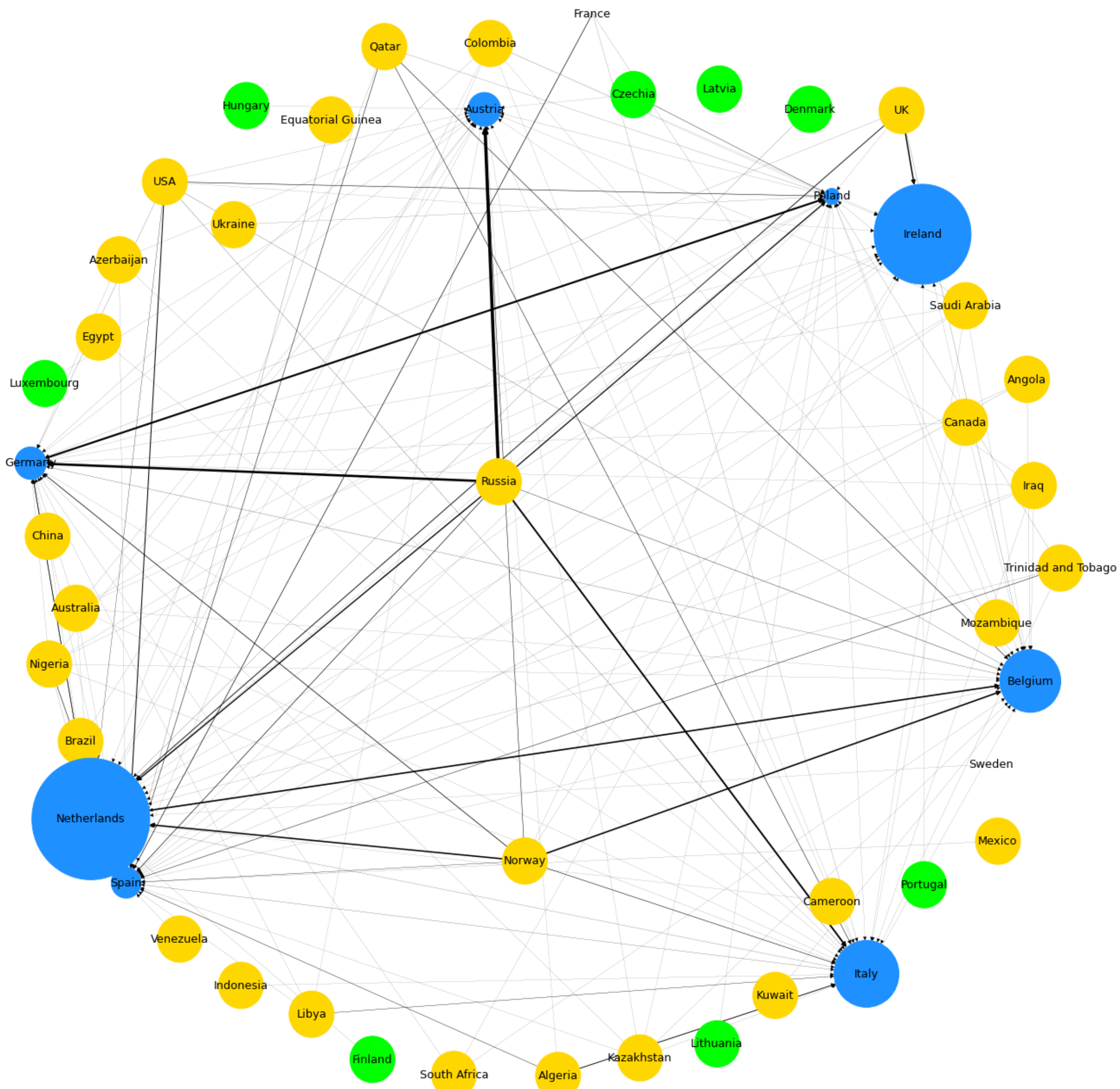


Figure 5: Impact of P2P on the top ten EU economies network

The figure reports the impact of the P2P simulation on the network of the top ten EU economies. On the left, it is reported the network prior to the simulation whereas, on the right, the network following the simulation is reported. The three main results are: a decrease in the number of edges, an increase in the average edge weight and a decrease in the average degree of each node.

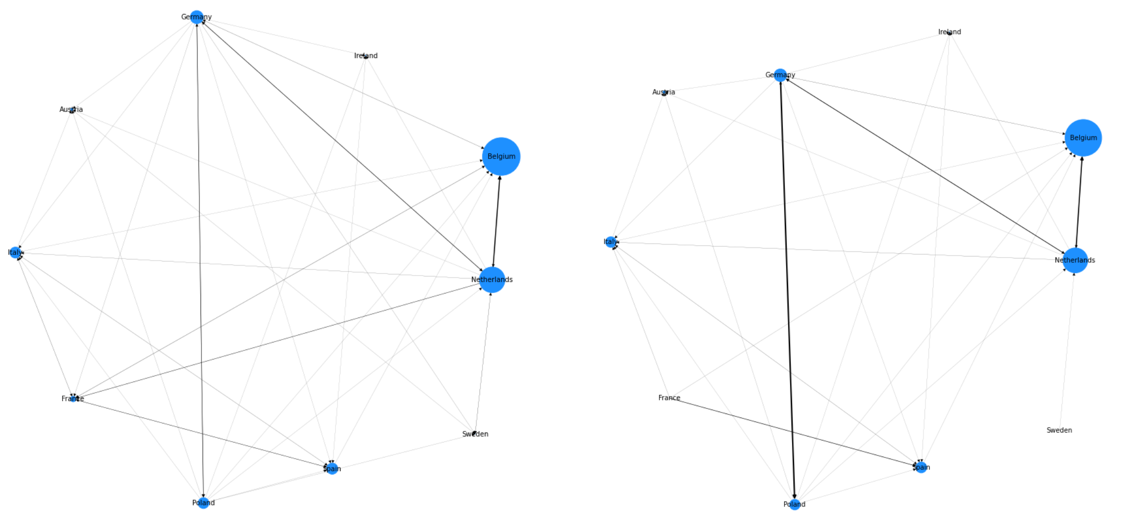


Figure 6: Impact of P2P on the EU network

The figure reports the impact of the P2P simulation on the EU network. On the left, it is reported the network prior to the simulation whereas, on the right, the network following the simulation is reported. The three main results are: a decrease in the number of edges, an increase in the average edge weight and a decrease in the average degree of each node.

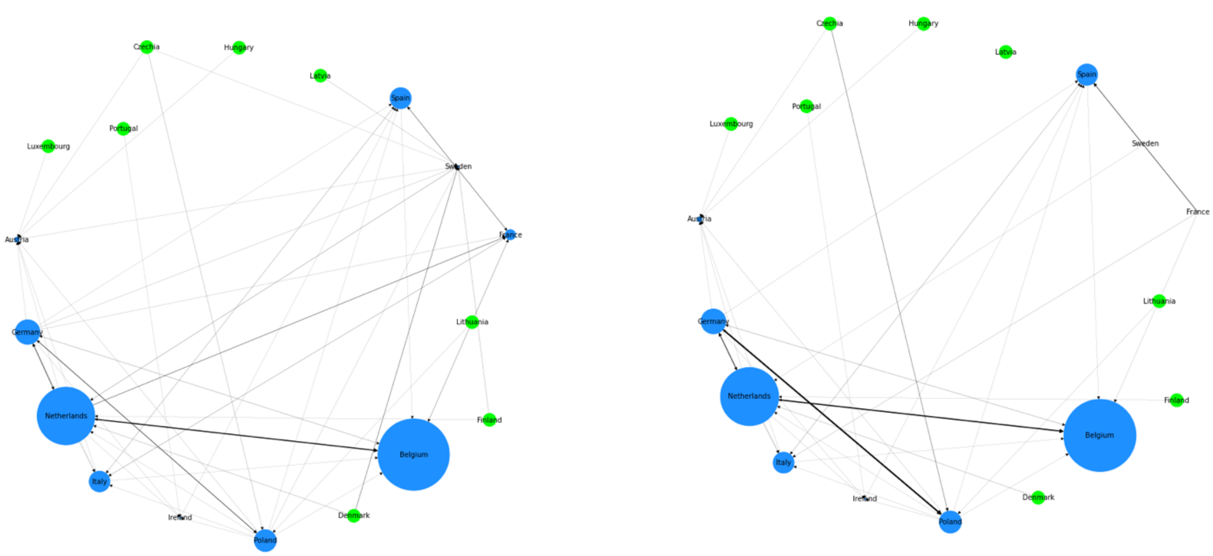


Figure 7: Impact of P2P on the non-EU network

The figure reports the impact of the P2P simulation on the non-EU network. On the left, it is reported the network prior to the simulation whereas, on the right, the network following the simulation is reported. The three main results are: a decrease in the number of edges, a decrease in the average edge weight and a decrease in the average degree of each node.

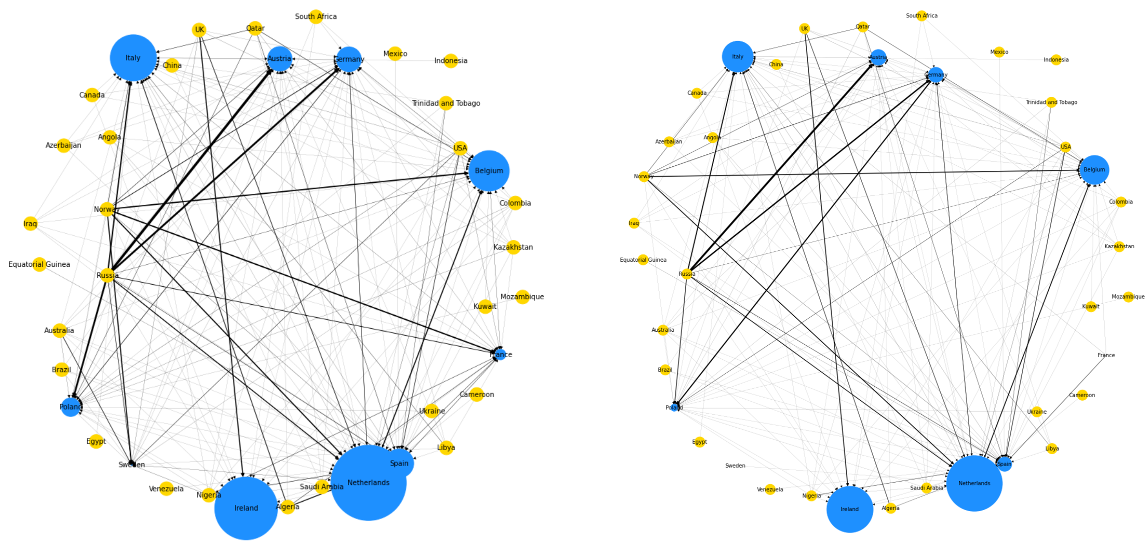


Table 2: OLS regression results on energy produced

The table below shows the coefficients of the OLS regression that was run on the electricity generated from each country.

log_electricity	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
probability_detached	22.615	2.969	7.62	0	16.782	28.447	***
detached_thresh	-.276	.024	-11.41	0	-.324	-.229	***

sun_hours	.236	.026	9.08	0	.185	.287	***
subsidy	.695	.057	12.09	0	.582	.808	***
environmentalism	-20.265	.554	-36.61	0	-21.352	-19.177	***
rainy	-9.934	.5	-19.89	0	-10.915	-8.953	***
cloudy	-7.45	.355	-20.96	0	-8.149	-6.752	***
density	-1.552	.196	-7.91	0	-1.937	-1.166	***
population	.002	.001	2.75	.006	.001	.003	***
Constant	28.757	.591	48.64	0	27.596	29.918	***

Mean dependent var	9.944	SD dependent var	1.190
R-squared	0.945	Number of obs	540
F-test	1010.999	Prob > F	0.000
Akaike crit. (AIC)	173.908	Bayesian crit. (BIC)	216.824

*** p<.01, ** p<.05, * p<.1

Table 3: Correlation table

The table below shows the correlations between the different features of the ABM model.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) sun_hours	1.000									
(2) subsidy	-0.385	1.000								
(3) environmentalism	0.151	-0.465	1.000							
(4) sunny	0.851	-0.188	0.237	1.000						
(5) cloudy	-0.524	0.075	-0.434	-0.790	1.000					
(6) rainy	-0.752	0.215	0.139	-0.673	0.078	1.000				
(7) density	-0.278	0.533	-0.214	-0.106	-0.213	0.429	1.000			
(8) log_electricity	0.627	0.199	-0.539	0.618	-0.227	-0.731	-0.058	1.000		
(9) population	0.439	0.153	-0.502	0.330	0.013	-0.552	-0.110	0.707	1.000	
(10) avg_price	0.036	0.342	0.384	0.039	-0.017	-0.044	-0.143	-0.118	0.178	1.000

Table 4: OLS regression results on environmentalism

The table below shows the coefficients of the OLS regression that was run on environmentalism.

environmentalism	Coef.	St.Err.	t-value	p-value	[95% Conf Interval]	Sig

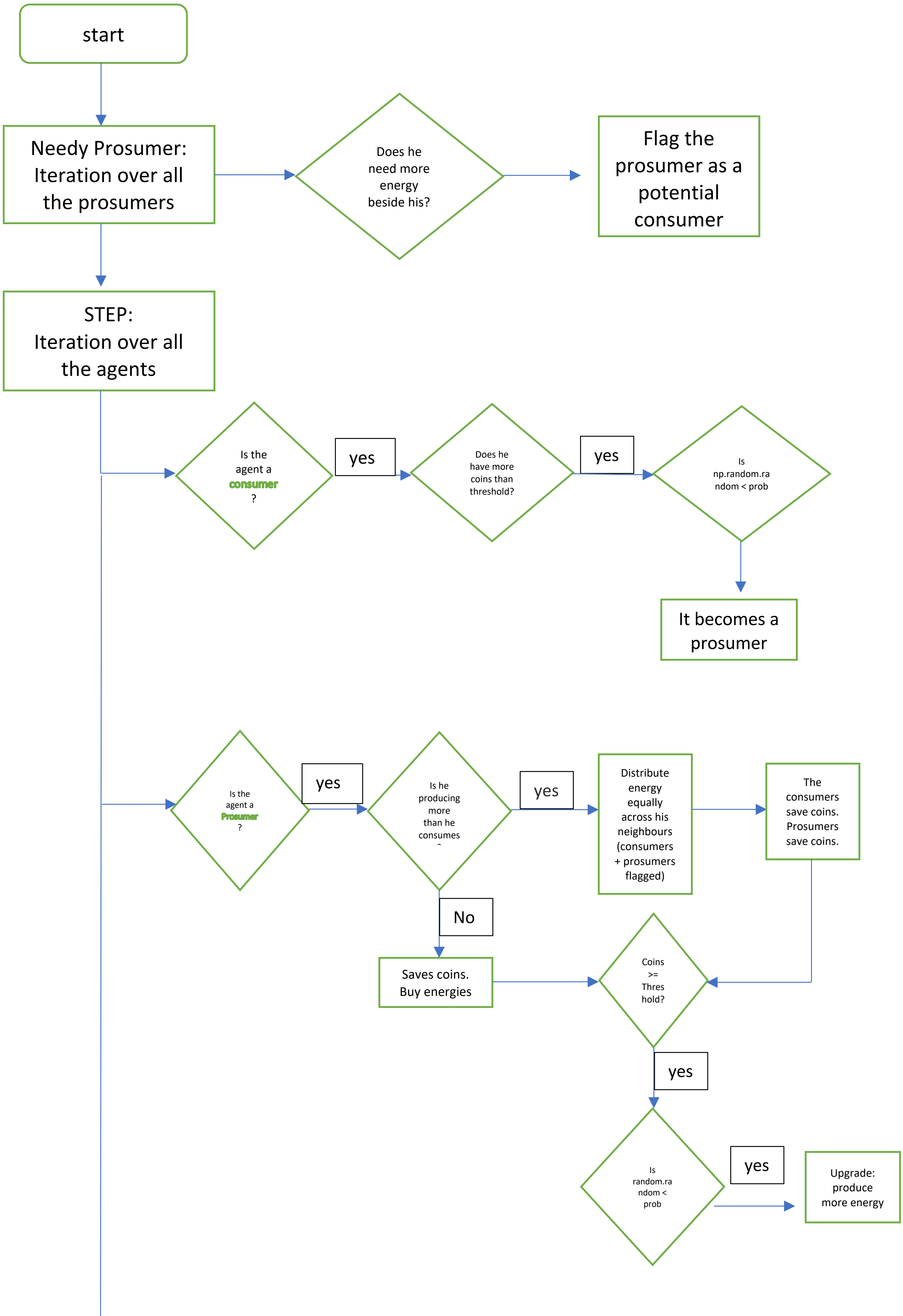
probability_detached	0	.055	-0.00	1	-.109	.109	
subsidy	-.087	.001	-70.83	0	-.089	-.084	***
detached_thresh	0	0	0.00	1	-.001	.001	
sun_hours	-.01	0	-19.41	0	-.011	-.009	***
rainy	-.124	.01	-13.00	0	-.143	-.105	***
cloudy	-.286	.006	-47.95	0	-.297	-.274	***
density	.054	.004	13.85	0	.046	.062	***
population	-.001	0	-51.84	0	-.001	-.001	***
avg_price	451.364	4.793	94.17	0	441.948	460.779	***
Constant	.749	.007	112.91	0	.736	.762	***

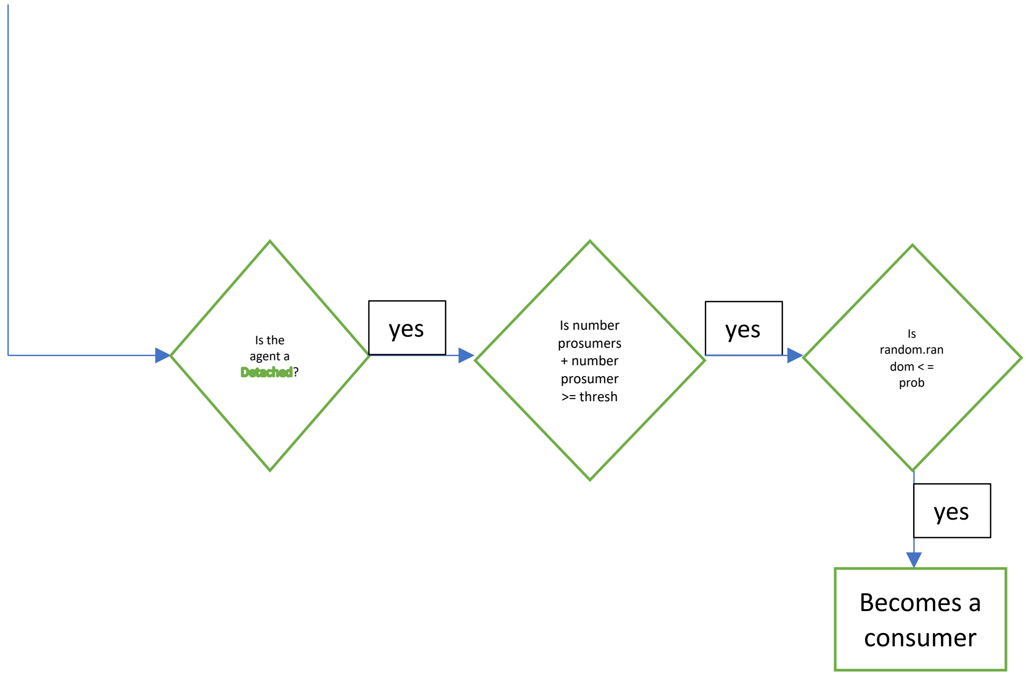
Mean dependent var	0.679	SD dependent var	0.035
R-squared	0.978	Number of obs	540
F-test	2617.697	Prob > F	0.000
Akaike crit. (AIC)	-4127.374	Bayesian crit. (BIC)	-4084.458

*** *p<.01*, ** *p<.05*, * *p<.1*

Flow Chart

The following scheme represents the ABM's underlying structure.




Is the agent a Detached?
yes
Is number prosumers + number prosumer >= thresh
yes
Is random.random < = prob
yes
Becomes a consumer